Speckle Noise Reduction in Ultrasound Images using Fuzzy Shrinking Technique

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Abstract

An ultrasound image provides the radiologist with noninvasive, low cost, and real-time images that can help them in diagnosis, planning and therapy. However, low PSNR (picture signal to noise ratio) in ultrasound images causes difficulties in correct interpretation of ultrasound images. Further, speckle noise present in ultrasound images is considered to be the major cause of its low PSNR. In this paper, a fuzzy-based system is proposed for reducing the speckle noise and making the images capable in diagnosing abnormal tissues and masses. An adaptive fuzzy complex diffusion speckle denoising (AFCDSD) model is combined with fuzzy shrinking for speckle noise removal. The proposed system is compared with some existing techniques using PSNR. The results show that adaptive fuzzy complex diffusion when combined with fuzzy shrinking outperforms other filters in terms of high PSNR.

Keywords: Complex diffusion, Fuzzy Shrinking, Speckle Noise, Ultrasound, denoising.

1. Introduction

Ultrasound imaging is widely used in the field of medical diagnostics due to its inexpensive, non-invasive and non-radiation properties [1]. Speed, low cost and portability of scanning machine make it a useful tool for medical diagnosis. It provides images in real time and allows high acquisition rates. The main problem of ultrasound imaging is speckle noise which is introduced due to the coherent nature of waves transmitted. Speckle degrades both the spatial and contrast resolution of an image thus resulting in improper diagnosis of an image. Reduction of speckle noise from ultrasound image is an important preprocessing step in medical image processing. Speckle reduction means to remove the distracting speckle pattern in ultrasound image without reducing the detail such as boundaries and edges in the ultrasound image. Removal of speckle noise is also important before feature extraction, region-based detection, analysis and segmentation. Speckle should be removed in such a way that fine details of image are preserved.

Many techniques are used to remove speckle noise from ultrasound medical images. Despeckling can be done either in frequency domain or spatial domain. Linear filter such as mean filter are not much suitable for speckle noise removal because they eliminate the high frequencies and thereby tend to smooth out the image edges. Median filters are the most popular non-linear filters they are extensively used to eliminate speckle noise because of its computational efficiency. But the drawback of median filter is smoothing of images. The Lee and Kuan filter have same formation although signal model assumption and the derivations are different [2,3]. Both the Lee and Kuan filters form an output image by computing a linear combination of the center pixel intensity in a filter window with the average intensity of the window [4]. The adaptive weighted median filter can effectively suppress noise but it fails to preserve useful details. The Frost filter also strikes a balance between the averaging and all-pass filter. Dutt [5] developed a homomorphic approach, in which multiplicative noise was converted into additive noise, and then Wiener filter was applied.

In the past few decades, wavelet-based denoising technique have gained much attention by researchers [6]. Performance comparison of all such techniques is also carried out [7]. Modified median based filter proposed by shrinivasan and Ebenezer [8] incorporated a decision-based technique in which the corrupted pixels are replaced by either the median pixel or neighborhood pixel. More
Recently, the Gamma maximum a posteriori (MAP) and extended version of the Lee and Frost filter have been introduced to alter performance locally according to three cases [9]. In the first case pure averaging is induced when the local coefficient of variation is below a lower threshold. Above a higher threshold the filter performs as a strict all pass filters. When the coefficient of variation exists in between the two thresholds, a balance between averaging and the identity is computed. Chirungrueng and Suvichakorn suggested a new filter, referred to as the 2-D weighted Savitzky-Golay filter, which could achieve at least the same level of speckle reduction as the median filter, but with far less computational time. This filter is suitable for filtering problems with large windows.

In this paper a hybrid filter is presented for removal of speckle noise in ultrasound images. This model consists of adaptive complex diffusion filter with fuzzy shrinkage rules. It comprises of fuzzy if then rules and aims at removing the speckle noise while preserving edge information and spatial resolution.

2. Related work

Many techniques have been developed to remove the speckle noise. Anisotropic diffusion is one of the popular techniques for removal of speckle noise. It was initially introduced by [10] and has been improved in several manners. Some of the drawbacks of anisotropic diffusion filters are blocky effects in images, destroy structural and spatial neighborhood information [11] and are slow in reaching a convergence point.

To overcome the disadvantages hybrid variety of filters were developed [12]. Hybrid model produce better result when compared to stand alone anisotropic filter, they come with defect of removing finer details of an image like edges, sharp corners and thin lines [13]. The Rajan hybrid model make use of fourth order partial differential equation (PDE) anisotropic diffusion and a relaxed median filter [14]. This model reduce the speckle noise with less blocking artifacts but drawback is slow convergence to remove the noise. Another hybrid model named WEAD (Wavelet embedded anisotropic diffusion) was proposed which combines Bayes shrink with anisotropic diffusion [15]. This method was able to reduce the blocking artifacts and fast the convergence. Bayes shrink cut the frequencies above the threshold resulting in fast convergence.

WASD (hybrid model) for speckle noise reduction combines fourth order PDE (partial differential equation) Anisotropic diffusion with SRAD (Speckle reducing anisotropic filter) with Bayes shrink [16]. In this method blocking artifact is reduced by reducing the number of iteration required to reach a convergence point. SRAD filter is used to reduce the blocking artifacts and improve the quality of the image.

3. Proposed work

Proposed model is a hybrid model that combines adaptive fuzzy complex diffusion despeckling filter with fuzzy shrinkage technique. The main objective of this model is to reduce the blocking artifacts (appearance of high frequency components) by reducing the number of iterations required to reach a convergence point. The iteration continues till the input image ‘z’ is converged to output image ‘Z’. The proposed Model is a two step process as shown in figure 1:

![Fig 1: Proposed AFCDS Model](image)

2.1 Adaptive complex diffusion filter

Adaptive complex diffusion filter comprises of non-linear equations with real and imaginary part. Diffusion filters are used to soften images. It diffuses strong light without affecting the sharpness and contrast of an image.

The general nonlinear anisotropic complex diffusion process [17, 20] looks for the solution of

\[
\frac{\partial I}{\partial t} = \nabla \cdot (D \nabla I)
\]

(1)

Where \( \nabla \cdot \) is the divergence and \( \nabla \) is the gradient and \( D \) is the diffusion coefficient. This equation was discretized by a forward in time and centered in space (FTCS) finite difference scheme; it is based on central difference in space and the forward Euler method in time. It gives first order convergence in space and second order convergence in time, so here second order is taken for convergence in time

\[
I_{i,j,m}^{(n+1)} = I_{i,j,m}^{(n)} + \Delta t^{(n)} \left( \nabla h^{(n)} D_{i,j}^{(n)} \nabla h^{(n)} I_{i,j,m}^{(n)} + \nabla h^{(n)} D_{i,j}^{(n)} \nabla h^{(n)} I_{i,j,m}^{(n)} \right)
\]

(2)

where \( \Delta h \) and \( \nabla h \) are, respectively, the discrete laplacian and gradient operators, \( \Delta t^{(n)} \) is the step in time for iteration \( n \), and \( i, j \) and \( m \) are the indexes for the voxels of \( I \) (\( i \) and \( j \) only for 2D images) and in 2D

\[
D_{i,j}^{(n)} = \frac{4D_{i,j}^{(n)} + D_{i,j}^{(n)} + D_{i,j}^{(n)}}{8}
\]

(3)

while in 3D

\[
D_{i,j,m}^{(n)} = \frac{6D_{i,j,m}^{(n)} + D_{i,j,m}^{(n)} + D_{i,j,m}^{(n)} + D_{i,j,m}^{(n)}}{12}
\]

(4)
Assuming that \( 0 \leq \left| \text{Im}(D_{i,j,m}^{(n)}) \right| \leq \text{Re}(D_{i,j,m}^{(n)}) \), for all \( i, j, m, n \) it can be shown [18,20] that this explicit method is stable if

\[
\Delta_t^{(n)} = \frac{1}{\alpha \max \left[ \left| \text{Im}(D_{i,j,m}^{(n)}) \right| + \text{Re}(D_{i,j,m}^{(n)}) \right]}
\]

where \( \text{Im}(u) \) and \( \text{Re}(u) \) stands respectively for the imaginary part and the real part of a complex number \( u \) and \( \Delta_t \) is responsible for convergence rate of the diffusion process. Here as in [20] we consider \( \Delta(x) = \Delta(y) = 1 \), and \( \alpha = 4 \) for 2D images and \( \Delta(x) = \Delta(y) = \Delta(z) = 1 \), and \( \alpha = 6 \) for volumes. Further the diffusion of coefficient used is given by [17, 20]

\[
D = \frac{\exp(i\theta)}{1 + \left( \frac{\text{Im}(I)}{k\theta} \right)^2}
\]

where \( i^2 = 1 \), \( k \) is a threshold parameter, \( \theta \) is phase angle close to zero and 1 is the image. Further it is illustrated in [19] that diffusion takes place in smooth areas and stops down at image edges. The diffusion coefficient can be thus approximated by

\[
D = \frac{1}{1 + \left( \frac{\Delta I}{k} \right)^2}
\]

The choice for the \( k \) parameter is important, as it modulates the spread of the diffusion coefficient in the vicinity of its maximum, that is, at edges and homogeneous areas, where the image laplacian vanishes. This parameter is adopted from [20]. From the above equations it is clear that the choice of diffusion coefficient and time step function are important, as diffusion coefficient decides which area is to be smoothed. Number of iterations depends on time step function, and number of iteration need to be reduced to reach the convergence quickly, so time step function and diffusion coefficient are important consideration.

2.2 Fuzzy Shrinking

In Fuzzy Shrinking, fuzzy rule based on fuzzy features have been used selecting various parameters [21]. Another approach to manage uncertainty is the concept of fuzzy sets, first introduced by Zadeh in 1965 [22]. Fuzzy rules are linguistic IF-THEN constructions that have the general form “IF A THEN B”, where A and B are (collections of) propositions containing linguistic variables. A is called the premise or antecedent and B is the consequence of the rule [23]. Fuzzy logic is able to modeling ambiguity, supervising uncertainty and also to support manual interpretation.

Noise variance \( \hat{\sigma}^2 \) is estimated using median estimator as in [24]. In order to increase the convergence speed constant is changed according to fuzzy rule and \( \alpha = \frac{4}{\text{if}} \) for 2D images and \( \alpha = \frac{6}{\text{if}} \) for 3D images. In order to implement our fuzzy-shrink method, two parameters (constant and level of diffusion), must be defined. These two parameters are directly related to the estimated noise variance (using median estimator). Therefore we use an adaptive method for selecting the parameters. Indeed this method is a simple IF THEN Fuzzy rule which assigns smaller and smaller level of diffusion when the estimated noise variance is small and vice versa. \( T_{\text{MAX}} \) is the maximum time taken by the diffusion process. Table 1 shows the choices for and level of diffusion in the different noise variances, which are obtained using test images and trial and error.

4. Results

In this section, we compare proposed hybrid filter with some of the best state-of-the-art techniques. Experiments were conducted to evaluate the proposed Model and compared with some of the best state of the art techniques. The fidelity criteria used was PSNR (Peak Signal to noise ratio), PSNR is a quality measurement between the original image and a denoised image. Higher the PSNR, better is the quality of denoised image. PSNR is calculated by the following equation:

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

and MSE is calculated by

\[
\text{MSE} = \frac{\sum_{M,N} (I_1(m,n) - I_2(m,n))^2}{M \times N}
\]

where \( M \) and \( N \) and \( m \) and \( n \) are number of rows and columns in the input and output image respectively. Experiments were conducted on twenty breast ultrasound images collected from various hospitals in Raipur (Chhattisgarh). Figure 2(b-f) shows results of various state of art filters when applied to breast ultrasound image of figure 2(a). Evaluation of different ultrasound images corrupted by speckle noise. PSNR was used as evaluation metrics. Table 2 shows the average PSNR of various filters and proposed filter in this study. Results show that adaptive fuzzy complex diffusion when combined with fuzzy shrinking outperforms other filters in terms of high PSNR of 30.06.
Table 1 Fuzzy Rule

<table>
<thead>
<tr>
<th>Estimated Noise Variance</th>
<th>$0 \leq \hat{n} \leq 10$</th>
<th>$10 \leq \hat{n} \leq 20$</th>
<th>$20 \leq \hat{n} \leq 30$</th>
<th>$30 \leq \hat{n} \leq 40$</th>
<th>$40 \leq \hat{n} \leq 50$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant $\phi$</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Level of Diffusion</td>
<td>$T_{\text{MAX}} \times 0.70$</td>
<td>$T_{\text{MAX}} \times 0.75$</td>
<td>$T_{\text{MAX}} \times 0.80$</td>
<td>$T_{\text{MAX}} \times 0.90$</td>
<td>$T_{\text{MAX}} \times 1$</td>
</tr>
</tbody>
</table>

(a). Original noisy image  (b). Output of Kaun filter  (c). Output of Lee filter  
(d). Output of Median filter  (e). Output of Mean filter  (b). Output of Proposed filter

Fig 2. Original noisy image and filtered image results

Table 2: Performance Evaluation (PSNR)

<table>
<thead>
<tr>
<th>Serial No</th>
<th>Filter</th>
<th>PSNR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Kuan</td>
<td>11.88</td>
</tr>
<tr>
<td>2</td>
<td>Lee</td>
<td>22.65</td>
</tr>
<tr>
<td>3</td>
<td>Median</td>
<td>26.12</td>
</tr>
<tr>
<td>4</td>
<td>Mean</td>
<td>27.32</td>
</tr>
<tr>
<td>5</td>
<td>Proposed</td>
<td>30.06</td>
</tr>
</tbody>
</table>

5. Conclusion and future scope

In this paper, we propose hybrid fuzzy based complex diffusion filter for speckle suppression in ultrasound images. We compared proposed filter with some of the best state-of-the-art techniques. Experiments were conducted on twenty breast ultrasound images. PSNR (Peak Signal to noise ratio) was used to evaluate various filters. The combination of the diffusion filter and fuzzy paradigms permits us to exploit the effectiveness of fuzzy reasoning and the ability converges fast. Results show that adaptive fuzzy complex diffusion when combined with fuzzy shrinking outperforms other filters giving highest PSNR. The proposed method can be easily extended to multiple dimensions and used for multidimensional filtering, enhancement, preprocessing step for segmentation and feature extraction, and visualization applications.

References


