SPECKLE NOISE REMOVAL IN ULTRASOUND IMAGES[3]

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Abstract

Ultrasound (US) images are useful in medical diagnosis. US is preferred over other medical diagnosis technique because it is non-invasive in nature and has low cost. The presence of speckle noise in US images degrades its usefulness. A method that reduces the speckle noise in US images can help in correct diagnosis. This method also should preserve the important

structural information in US images while removing the speckle noise. In this paper, a method for removing speckle noise using a combination of wavelet, total variation (TV) and morphological operations has been proposed. The proposed method achieves denoising by combining the advantages of the wavelet, TV and morphological operations along with the utilization of adaptive regularization parameter which controls the amount of smoothing during denoising. The work in this paper has the capability of reducing speckle noise while preserving the structural information in the denoised image. The proposed method demonstrates strong denoising for synthetic and real ultrasound images, which is also supported by the results of various quantitative measures and visual inspection.

1 Introduction

There are many methods which are used for medical diagnosis out of which Ultrasound (US) imaging is the most widely used method which has the benefit over other medical diagnostic methods, as the acquisition of these images are easy and less costly. While obtaining an US image, it gets corrupted with speckle noise[2] . Generation of speckle noise is due to the interference of beams reflected towards the transducer, which causes a granular artifact to appear in the image. Due to the speckle noise, the important structural information contained in the US image gets corrupted and thus the examiner may not be able to interpret the image correctly. Speckle noise also contributes to low image resolution and contrast which further leads to poor quality of US images. Thus, removing the speckle noise from US images is an important step . The US are sound waves above 20 kHz, which exceed the audible frequency range. For medical US imaging, the range is between 2 and 18 MHz. The pulse-echo effect is used in US imaging, the steps of which are transmitting, listening and receiving. Initially, the ultrasonic pulses are transmitted into the organ via a transducer. After the pulses hit an organ boundary, these are reflected back from the tissues. These reflected echoes are processed to form an image. But, there are certain echoes that get scattered which then results in an interference pattern called speckle noise .

2 Literature Review

Over many years, research on speckle noise reduction has been done on a wide scale. For removal of noise, linear and non-linear filters have been used. Non-linear filters work on the concept of Partial Differential Equations while linear filters work on the concept of averaging. Non-linear filters generally contain methods based on diffusion such as isotropic diffusion, anisotropic diffusion, and total variation (TV). Some linear filters are Median filter, Nonlocal-Means filter and Lee filter. For image filtering, there are also multiscale spatial filtering methods which contain wavelet, curvelet and ridgelet transform.

For speckle noise reduction in US images wavelets have been extensively used. Wavelet uses the concept of decomposing the images and then working on its component for noise removal and then assembling it back into the original image without loss of information. The Efficiency of wavelets in removing speckle noise makes it a good filter. The related work done in the speckle noise removal using wavelets in recent years are mentioned below:
In the year 2001, Achim et al. introduced a multiscale nonlinear homomorphic method for speckle reduction in US images which used log transform and wavelet transform for noise

removal along with the use of Bayesian estimator[1] .In the year 2004, Gupta et al. developed a method that used the wavelet transform with Generalized Gaussian Distribution. They used sub-band modeling and used soft thresholding to threshold the wavelet coefficients.In the year 2009, Sudha et al. developed a method that used thresholding method using wavelets for speckle noise reduction [5]. In the year 2011, Sarode and Deshmukh used the concept of Discrete Wavelet Transform (DWT) for removal of speckle noise and calculated threshold for sub-band coefficients [4].

3 Motivation to Work

Speckle noise contributes to low image resolution and contrast, which leads to poor quality of US images. Before analyzing the US image, speckle noise reduction becomes an important pre-processing step. What becomes more important in case of US images is that, the important structural information needs to be preserved. The loss of this information can lead to an incorrect analysis of images or misinterpretation by the examiner. Our main motivation for this work is to reduce speckle noise and focus on maintaining the structural information of the denoised image, along with improving performance evaluation parameters. To achieve this objective, wavelet is used, as wavelet transforms enhance texture and organ surfaces along with denoising. Some amount of denoising can be achieved by wavelets but it is not very efficient if used alone. Thus, TV function has also been used because the amount of denoising achieved by TV function is high and it is capable of removing most of the speckle noise from the US image. Also, it helps in defining shapes and objects in medical imaging. While using TV we may have to deal with its sensitivity to the number of iterations and over-filtering, which may result in the loss of relevant information from US images. To deal with the problem of the number of iterations, two optimization techniques: Newton method and Chambolle method have been used. Over-filtering is removed by making the regularization parameter lambda adaptive which is used in the TV function. The regularization parameter lambda controls the amount of smoothing applied to the image and it is generally set to a fixed value. The fixed value of lambda causes the same amount of smoothing applied to all the images which is not very fruitful. This parameter has been made adaptive so that the amount of smoothing applied is different for all the images used. The value of lambda is obtained from multi wavelet decomposition and using the information from its sub-band HH1 using the median estimator. Thus, it will produce a different value of λ according to the amount of noise present in that image. Morphological operations have been used to ensure that the image quality index of US images is maintained, which can be verified by the higher value of UQI parameter. Median filter has been used to maintain the image contrast and the overall image quality. The output is that we get better speckle reduction method which ensures that the structural information of US image is preserved and the denoised image has better parameter value.

The US images that have been taken into consideration in this paper are real kidney US images and carotid artery US images. The kidney is a deeper structure organ in the human body, thus there are chances of more reflections of the ultrasonic pulse while returning to the transducer which results in more speckle contents. Similarly, in case of carotid artery images, there are more edges present. Thus, these two datasets help in achieving the objective during performance evaluation of the proposed method and we are able to judge through visual analysis that how much structural information is preserved.

4 Datasets

The dataset containing carotid artery images have been collected from here . We have used real US images carotid artery because these images contain more structural information like edges in case of the carotid artery. Here, is a sample image from the dataset

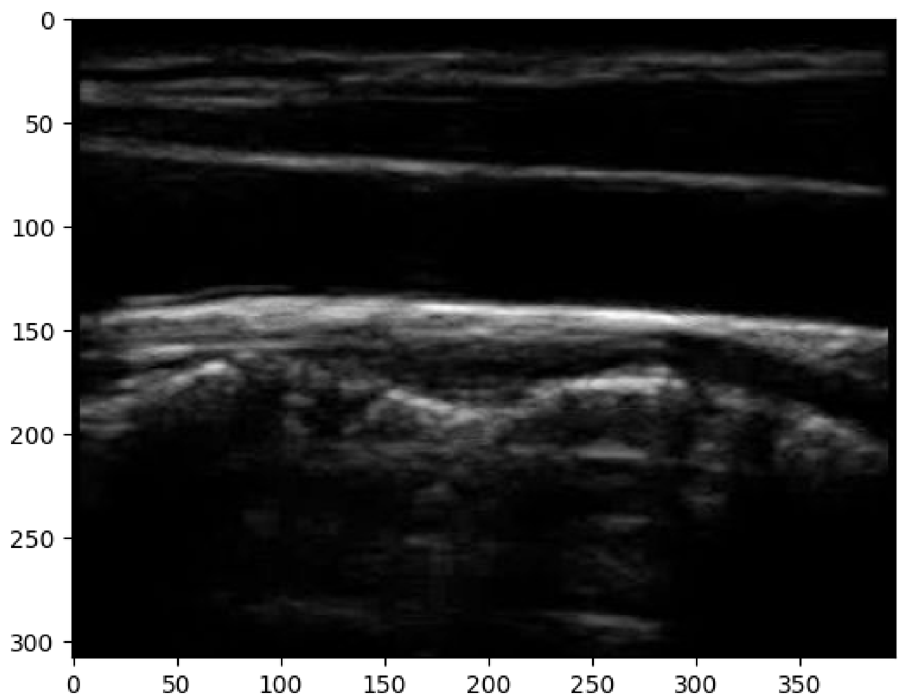


Figure 1: Sample Input image

5 Proposed Method

The following Process is followed for denoising the image in this paper

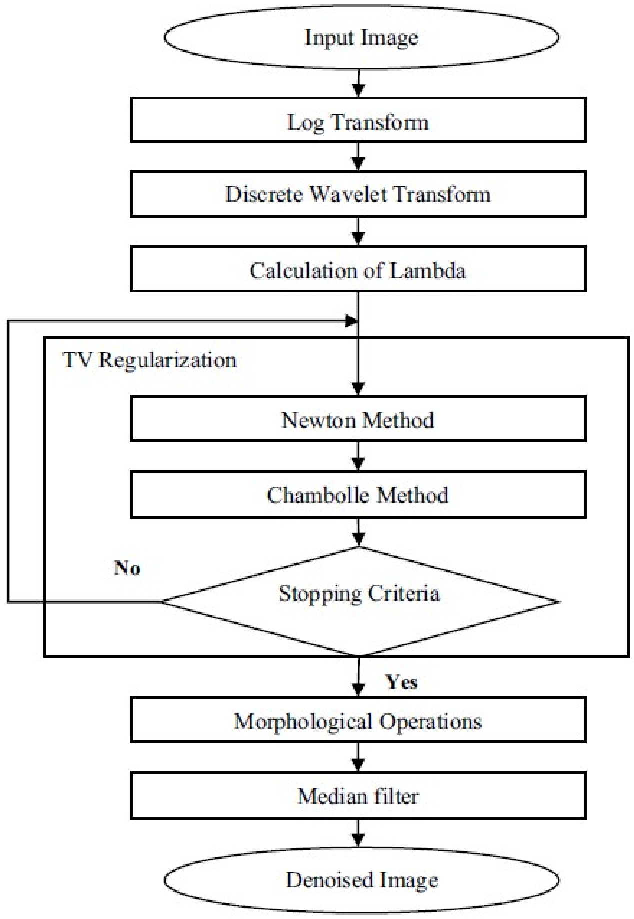


Figure 2: Proposed Method

5.1 Log transformation:

1. Speckle noise is multiplicative noise. For converting multiplicative noise to additive noise log transformation is applied. Additive noise is easier to remove than multiplicative noise because noise intensity does not vary with image intensity

   Multiplicative noise is shown as:
   M(r,s)= N(r,s)×p(r,s) eq(1)

   Additive noise is shown as:
   M(r,s)= N(r,s)+p(r,s) eq(2)
   Pixel coordinates of the 2D image are represented by (r,s) .
   M(r,s) represents the real US image,
   N(r,s) represents the denoised image and
   p(r,s) represents the speckle noise .
   Log transformation is shown as:
   $\log M = \log N + \log P$ eq(3)

2. The below is the image after performing log Transformation on the sample image.

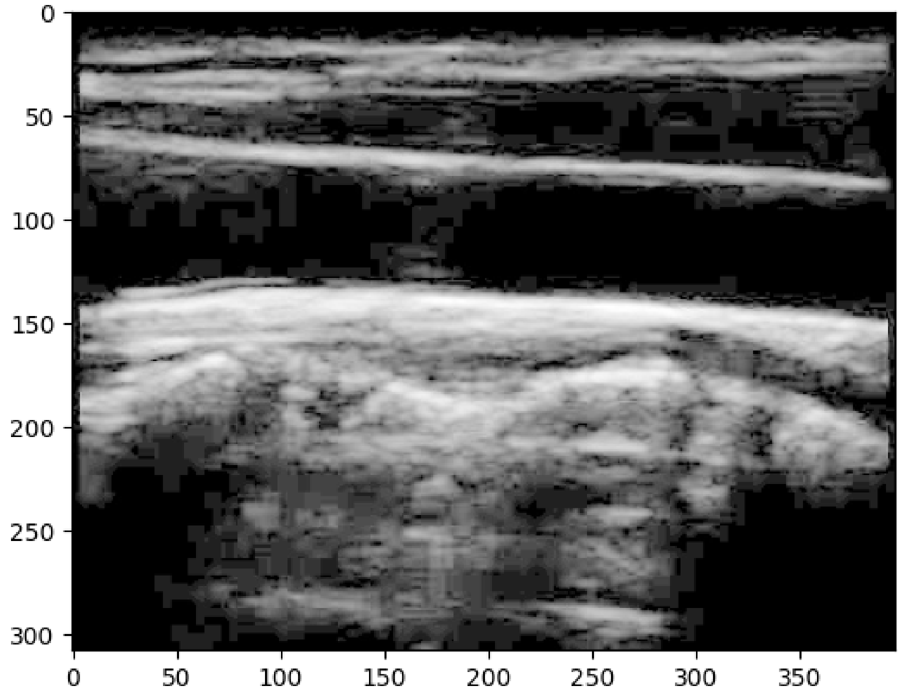


Figure 3: Image after implementing Log transformation

5.2 Wavelet transformation:

3. Wavelet transforms remove speckle noise and retains the detail in the image. There is DWT that corresponds to the decomposition of the image according to its level and inverse DWT for reconstruction of the image after the threshold is applied. The DWT application in an image results in sub-bands (LL, LH, HL and HH). These sub-bands are classified into details and approximation. The details sub-band are LHi, HLi, HHi and the approximation sub-band is LLi, where 'i' is the scale, from 1, 2. . . D, where D represents the total number of decompositions. Wavelet thresholding removes the noise by thresholding the detail sub-bands coefficients and keeping fixed the approximation sub-band coefficients .

   In the proposed method, DWT has been applied to the image from Step 1. Wavelet type 'Daubechies' with vanishing moment four and minimum scale three, has been preferred as it is considered to reduce the correlation between the data efficiently. Inverse DWT is applied to reconstruct the denoised image.

5.3 Total variation regularization:

4. TV represents the variation in the energy of an image with a function shown as:

$$\text{E(M,N)} = \left\| M - N \right\|_2^2 + \lambda |J_{TV}(N)| \text{ eq(4)}$$

   where E is the energy function. $\left\| . \right\|_2$ represents the Euclidean norm, which in general for a term 'f' can be represented as $\left\| f \right\|_2 = \sqrt{f_2^2 + ... + f_{2n}^2}$, where (1,2. . . n) denotes the n-dimensional Euclidean space . M and N are the noisy and denoised image respectively.

Lambda λ is the regularization parameter that is used to control the smoothing applied in an image. If λ is set to a higher value, the denoised image becomes over smoothed and blurred. When λ is set to a lower value there is less noise removal from the image. The selection of λ value is an important aspect as for every US image the amount of smoothing applied might be different.

In the proposed method, rather than fixing the value of lambda λ is obtained from multi wavelet decomposition of the image M by using the information from its first decomposition level diagonal sub-band HH1. The median estimator method is used to evaluate the noise variance. It does so by using the diagonal detail coefficients to calculate the absolute deviation, where 0.6745 is the median absolute deviation value.
Lambda is evaluated as:

$$\lambda = [\frac{median(|HH1|)}{0.6745}] \text{ eq(5)}$$

This Equation will produce a different value of λ according to the amount of noise present in the US image. The amount of smoothing will depend directly on the amount of noise thus removing the effect of blurring from the image. In the eq(4) $J_{TV}(N)$ computes the divergence of N, which is the partial derivative of its respective components .

Speckle noise present in the US image increase the energy of the function as shown in Eq. (4), so the denoised Image N is such that it is minimizing the energy of this function. The function obtained from total variation is convex, which indicates that it can converge to only one minimum .

In the proposed method, TV function is optimized by using two optimization methods. Energy function used is shown as:

$$|G(M)_{V \epsilon R^d}|_{min} = \frac{1}{2}\left\|V - N\right\|_2^2 + \lambda J(N) \text{ eq(6)}$$

For Eq. (6), M is used as a noisy image which is obtained from step 2 and V is the image which is minimizing the overall energy function. V is set equal to the size of the noisy image during the time of calculation of derivative. To solve this Newton method is used. Newton method optimization is a classical optimization technique which converges to a minimum value. The output from Newton method is provided as input for the function shown by Eq. (7).

$$|G(V)_{N \epsilon R^d}|_{min} = \frac{1}{2}\left\|V - N\right\|_2^2 + \lambda J(N) \text{ eq(7)}$$

For Eq. (7), V acts as noisy image and this function is solved by Chambolle method for convergence to a minimum value, resulting in the denoised image N.

After the convergence by Chambolle, M is updated to the N in Eq. (6), then the same procedure follows until the stopping criteria is fulfilled.

Newton method optimization is a classical optimization technique which converges to a minimum value. It uses Hessian matrix for first derivative and Jacobian matrix for the second derivative and is simple to use and implement. Chambolle projection optimization is an optimization technique which is used because of its fast convergence and confirms to converge to one minimum if the function used is convex . An advantage of using Chambolle optimization is that we do not need to regularize the TV energy function as done in Euler-Lagrange equations, in which to regularize the energy function we need to calculate this function: $f\sqrt{|\nabla V|^2+\epsilon^2}$, where ϵ is used to avoid numerical instabilities . The image shown below is generated after performing above given methods

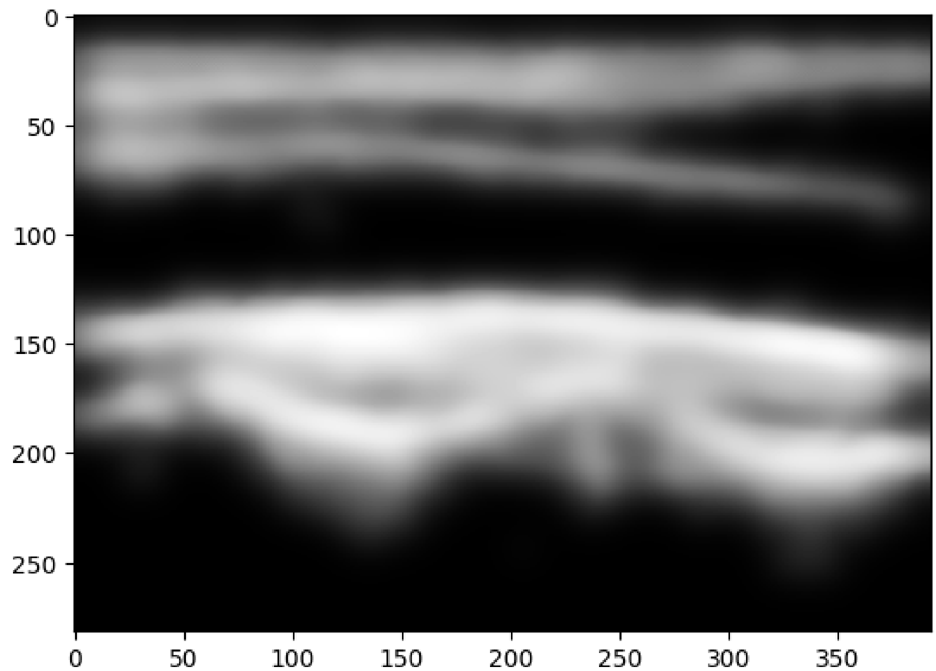
5. 

Figure 4: Image after performing wavelet transformation and Total variation regularization

5.4 Stopping Criteria:

6. Stopping criteria is fulfilled when outer loop reaches a maximum value that is three (K=3) or when the condition $\frac{\left\|N^{K+1}-N^K\right\|_2}{\left\|N^K\right\|_2} < 10^{-3}$ is satisfied. The inner loop for Newton method is fixed at 2 and for Chambolle is fixed at 8

5.5 Morphological operations:

7. Morphological operations are applied to enhance the image quality. The structuring element (SE) represented by 's', plays an important role in defining the object shape. The morphological operation erosion denoted by $\ominus$ is used to lighten the edges or boundaries in an image. Morphological operation dilation which is denoted by $\oplus$ is used to enlarge the boundaries in an image. Morphological opening denoted by Nos = (N$\ominus$S)$\oplus$ s is erosion followed by dilation and morphological closing denoted by N$\cdot$s=(N$\oplus$S)$\ominus$s is dilation followed by erosion . In the proposed method, morphological operation closing has been applied on the image obtained from step 3. The structuring element used is a rectangle of size 3$\times$3.

5.6 Median Filter

8. The Median filter uses the concept of averaging to remove the noise from images. While removing noise from images it also preserves the edges. It calculates the median of pixels within the window estimated and replaces the center pixel with this median value. This filter is much effective when there are strong spikes like component in the noise pattern . In the proposed method, the median filter has been applied to the image obtained from step 5. The window used is of size 3×3. The following is the final output after following the process

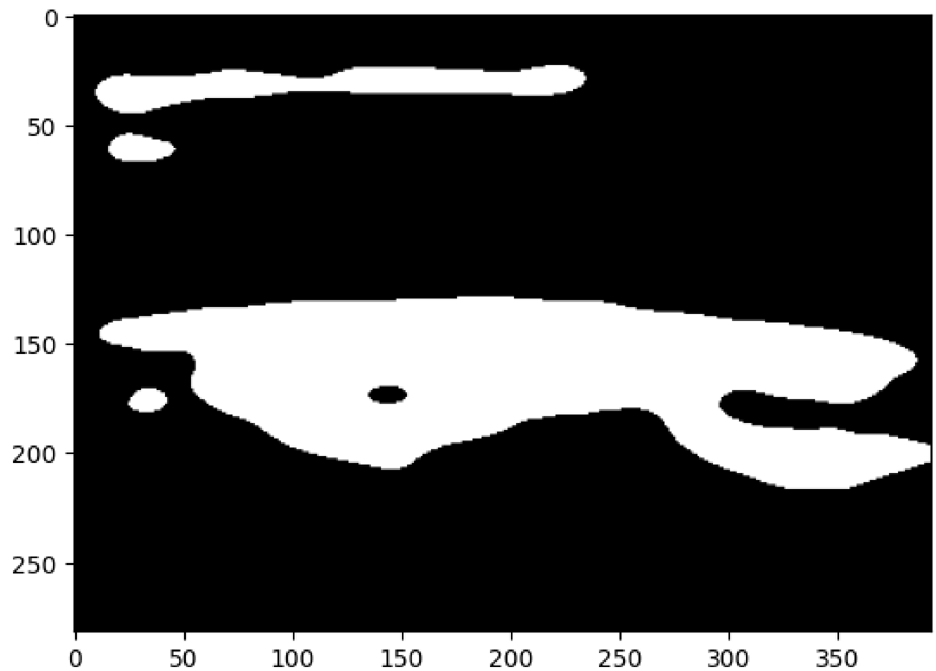


Figure 5: Denoised image

6 Conclusion:

The proposed method uses a combination of wavelets, total variation and morphological operations. The results obtained show that the proposed method is able to reduce speckle noise in an efficient manner as well as it performs well in preserving the important structural details in the US images.The amount of regularization done by the proposed method is accurate as it does not involve over blurring of the denoised image. The image quality of the image denoised by the proposed method in case of real ultrasound images is better than other methods. The features in real ultrasound images need to be preserved as these contain information, but the removal of speckle noise may also remove these important features. In this paper, the combination used in the proposed method has the benefit as the wavelet transform lead to enhanced texture and organ surfaces and the use of optimization methods for total variation has reduced the number of iterations. The morphological operations have the benefit of edge preservation while retaining the structure of the denoised image. The median filter maintains the contrast level of the denoised image. The proposed method ensures to preserve structural information in US images after denoising. With structural information preserved, the visual perception is improved and US images can be examined by experts in a better way.

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