COMPARATIVE STUDY OF SPECKLE NOISE REDUCTION FILTERS IN ULTRASOUND THYROID IMAGES

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ABSTRACT

Ultrasound imaging is a vital tool for diagnosis of thyroid gland as it provides information about the internal structure of the thyroid to detect abnormalities in tissues. Unfortunately, the presence of speckle noise in these images affects edges and fine details which limit the contrast resolution and make diagnostic more difficult. To overcome this drawback, speckle noise reduction in ultrasound thyroid image is essential to increase the quality of the image. This paper compares various speckle noise reduction filters such as Median, Fourier, Wavelet, Homomorphic and Homomorphic wavelet filter. The performance of the filters are compared based on evaluation metrics such as Peak Signal to Noise Ratio (PSNR), Mean Absolute Error (MAE) and Pearson Correlation Coefficient (PCC).

KEYWORDS: Ultrasound imaging, Speckle noise reduction, Contrast resolution
INTRODUCTION

Ultrasound is a sound wave with a frequency that exceeds 20 kHz. It transports energy and propagates through several means as a pulsating pressure wave (Suetens Paul, 2002). It is described by a number of wave parameters such as pressure density, propagation direction, and particle displacement. If the particle displacement is parallel to the propagation direction, then the wave is called a longitudinal or compression wave. Ultrasound technique is mainly based on measuring the echoes transmitted back from a medium when sending an ultrasound wave to it. In the echo impulse ultrasound technique, the ultrasound wave interacts with tissue and some of the transmitted energy returns to the transducer to be detected by the instrument (Yongjian Y et al., 2002). The use of ultrasound imaging in medical diagnosis is well established because of its non-invasive nature, low cost, capability of forming real time imaging and continuing improvement in image quality. However, the main drawback of the US image is poor quality of images, which are affected by speckle noise. Speckle is a form of multiplicative noise which appears as random mottling of the image with bright and dark spots which degrades the US images making visual observation quite difficult and limiting their diagnostic potential. Therefore, noise reduction is very important, as various types of noise generated limits the effectiveness of the system. There are two basic approaches to speckle reduction in US B-Scan images, one is spatial filtering method and the other one is transform-domain filtering method. The usual way of removing the speckle noise from US image is using the spatial filter technique but it works well only if the underlying signal is smooth. This paper analyses different filtering techniques based on statistical methods for the removal of speckle noise. Each filter is compared based on evaluation metrics such as Mean Absolute Error (MAE), Peak Signal to Noise ratio (PSNR) and Pearson Correlation Coefficient (PCC).

SPECKLE NOISE MODEL

Mathematically the image noise can be represented with the help of these equations below:

\[ v(x,y) = g[u(x,y)] + \eta(x,y) \]  
\[ g[u(x,y)] = \int \int h(x,y : x'y'),u'(x'y')dx'dy' \]  
\[ \eta(x,y) = f[g(u(x,y))][\eta_1(x,y) + \eta_2(x,y)] \]

Here \( u(x,y) \) represents the objects (means the original image) and \( v(x,y) \) is the observed image. Here \( h(x,y;x'y') \) represents the
impulse response of the image acquiring process. The term \( \eta(x,y) \) represents the additive noise which has an image dependent random components \( f[g(w)]\eta_1 \) and an image independent random component \( \eta_2 \). Speckle noise can be modeled as

\[
v(x,y)=u(x,y)s(x,y)+ \eta(x,y) \quad (4)
\]

Where the speckle noise intensity is given by \( s(x, y) \) and \( \eta(x, y) \) is a white Gaussian noise. A possible generalized model of the speckle imaging is

\[
g(n,m)=f(n,m)u(n,m)+\zeta(n,m) \quad (5)
\]

Where \( g, f, u \) and \( \zeta \) stand for the observed image, original image, multiplicative component and additive component of the speckle noise. Here \( (n,m) \) denotes the axial and lateral indices of the image samples or, alternatively, the angular and range indices for B-scan images (Jaspreet Kaur et al., 2013). When applied to ultrasound images, only the multiplicative component of the noise is to be considered and thus the model can be considerably simplified by disregarding the additive term, so that the simplified version of (5) becomes

\[
g(n,m)=f(n,m)u(n,m) \quad (6)
\]

SPECKLE NOISE REDUCTION FILTERS

In speckle filtering a kernel is being moved over each pixel in the image and applying some mathematical calculation by using these pixel values under the kernel and replaced the central pixel with calculated value. The kernel is moved along the image only one pixel at a time until the whole image covered. By applying these filters smoothing effect is achieved and speckle noise has been reduced to certain extent (Dainty J.C, 1971).

Median filter

The best known order statistics filter is the median filter in image processing. The median filter is also the simpler technique and it also removes the speckle noise from an image and also removes pulse or spike noise (Amandeep Kaur et al., 2010). Pulse functions of less than one-half of the moving kernel width are suppressed or eliminated but step functions or ramp functions are retained. The median filter considers each pixel in the image in turn and looks at its nearby neighbours to decide whether or not it is representative of its surroundings. Instead of simply replacing the pixel value with the mean of neighbouring pixel values, it replaces it with the median of those values. The median is calculated by first sorting all the pixel values from the
surrounding neighbourhood into numerical order and then replacing the pixel being considered with the middle pixel value.

**Fourier filter**

Fourier filtering is, naturally, based on fourier transform properties. In medical images, the objective is to find a filter or filtering function which will minimize fourier transform’s high frequency components (Prager R.W et al., 2002). Once this is done, the output image will be obtained by means of the inverse fourier transform. There are two types of filters: ideal filter and butterworth filter.

**Ideal filter**

Ideal filters allow a specified frequency range of interest to pass through while attenuating a specified unwanted frequency range. For an ideal filter, the attenuation for frequencies beyond the cut-off would be complete. The ideal filter is impossible to realize without also having signals of infinite extent in time, and so generally needs to be approximated for real ongoing signals, because the sinc function’s support region extends to all past and future times. The filter would therefore need to have infinite delay, or knowledge of the infinite future and past, in order to perform the convolution (Juan L. Mateo et al., 2009).

**Butterworth filter**

Butterworth filters are having a property of maximally flat frequency response and no ripples in the pass band. It rolls of towards zero in the stop band. Its response slopes off linearly towards negative infinity on logarithmic Bode plot. Like other filter types which have non-monotonic ripple in the passband or stopband, these filters are having a monotonically changing magnitude function with $\omega$. Butterworth filter has a slower roll off when comparing with chebyshev type I/type II filter or an elliptic filter. Hence for implementing a particular stopband specification it will require a higher order. The response of an n-order Butterworth low pass filter is given by

$$R(\omega) = \frac{1}{1 + \xi^2 C_n(\frac{\omega}{\omega_c})^2}.$$  

$\xi$ is the ripple, $\omega_c$ is the cut off frequency, $C_n$ is the nth order Chebyshev polynomial.

**Homomorphic filter:**

Homomorphic filtering is a generalized technique for signal and image processing, involving a nonlinear mapping to a different domain in which linear filter techniques are applied, followed by mapping back to the
original domain. Homomorphic filter is sometimes used for image enhancement. It simultaneously normalizes the brightness across an image and increases contrast (Evans A.N., 1993) Homomorphic filtering is used to remove multiplicative noise. Illumination and reflectance are not separable, but their approximate locations in the frequency domain may be located.

Since illumination and reflectance combine multiplicatively, the components are made additive by taking the logarithm of the image intensity, so that these multiplicative components of the image can be separated linearly in the frequency domain. Illumination variations can be thought of as a multiplicative noise, and can be reduced by filtering in the log domain (N.K. Ragesh et al., 2011) To make the illumination of an image more even, the high-frequency components are increased and low-frequency components are decreased, because the high-frequency components are assumed to represent mostly the reflectance in the scene (the amount of light reflected off the object in the scene), whereas the low-frequency components are assumed to represent mostly the illumination in the scene. That is, high-pass filtering is used to suppress low frequencies and amplify high frequencies, in the log-intensity domain.

**Wavelet Filter**

Wavelets are basically mathematical functions which break up the data into different frequency components, and then we study each component with a resolution matched to its scale. Wavelets have some advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes. Wavelets are the better technique to handle the different type of noises which is present in an image (Sudha et al., 2009). There are different wavelet families which shown different results when they are applied in image processing field. Recently wavelets analysis is widely applied in the image de-noising due to its multi-resolution and locality property. An input signal frequency representation can be obtained using wavelet transform. The processing is carried out without implementing a very complex transform. It consists of eliminating certain frequencies in order to eliminate any existing noise. Since it is known that when an image is decomposed, the HH, LH, and HL images contain most of the image’s high frequencies and noise, one can eliminate the noise by eliminating those very images (Raghuveer M. Rao., 2001).
The following steps perform the wavelet decomposition of the US medical image: In the first stage of the decomposition, split the US image into 4 subbands, namely the HH, HL, LH (high pass) and LL (Low pass) subbands. The HH subband gives the diagonal information of the US image; the HL subband gives the horizontal features while the LH subband represents the vertical structures of the US image. The LL subband is the low-resolution residual consisting of low frequency components and this subband is further divided at the higher levels of decomposition. All the wavelet filters use wavelet thresholding operation for de-noising. Speckle noise is a high-frequency component of the image and appears in wavelet coefficients (Jaideva Goswami). One widespread method exploited for speckle reduction is wavelet thresholding procedure.

The steps involved in Wavelet based speckle reduction are:

- **Thresholding the wavelet coefficients**: (Threshold may be universal or subband adaptive), which defines a threshold of zero to the first wavelet coefficients while the other wavelet coefficients are shrunk accordingly.

- **Computation of the Inverse Discrete Wavelet Transform (IDWT)** to reconstruct the denoised image and to estimate the metrics of the denoised image.

For the threshold selection, soft thresholding has been chosen as the suitable method for noise removal algorithm to produce visually more pleasing images (D.L Donoho., 1995).

**EVALUATION METRICS**

The performance of each filter is evaluated quantitatively for thyroid ultrasound image using the quality metrics like Mean Absolute Error (MAE), Pearson Correlation Coefficient (PCC), and Peak Signal to Noise Ratio (PSNR).

**Mean Absolute Error (MAE)**

It is average of absolute difference between the reference image and test image (Thangavel K et al., 2009) which is given by the equation
MAE = \frac{1}{MN} \sum_{i=1}^{m} \sum_{j=1}^{n} |x(i,j) - y(i,j)| \quad (8)

Where M and N are the width and height of the image.

**Peak Signal to Noise Ratio (PSNR)**

The PSNR is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation (Pasi Franti et al., 1994). It is given by

\[
\text{PSNR} = 10 \log_{10} \frac{255^2}{\text{MSE}} \quad (9)
\]

The PSNR is higher for a better transformed image.

**Pearson Correlation Coefficient (PCC)**

The Pearson's method is widely used in statistical analysis, pattern recognition and image processing (A. Miranda Neto et al., 2013). It is given by the equation

\[
\text{PCC} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2} \sqrt{\sum(y_i - \bar{y})^2}} \quad (10)
\]

Where \(x_i\) is the intensity of the \(i^{th}\) pixel in image 1, \(y_i\) is the intensity of the \(i^{th}\) pixel in image 2, \(x_m\) is the mean intensity of image 1, and \(y_m\) is the mean intensity of image 2.

**RESULTS AND DISCUSSIONS**

Thus the thyroid nodule images are preprocessed for speckle noise reduction using various speckle noise reduction filters such as Median, Fourier, Homomorphic, Wavelet and Homomorphic Wavelet filter. The following figures shows the denoising results of speckle filtering in ultrasound thyroid images:

![Denoising results of speckle filtering in ultrasound thyroid images](image_url)

**Figure 1**: Denoising results of speckle filtering in ultrasound thyroid images (a) Original ultrasound image of thyroid (b) Median filter (c) Fourier ideal filter (d) Fourier butterworth filter (e) Wavelet filter (f) Homomorphi ideal filter (g) Homomorphic butterworth filter (h) Homomorphic wavelet filter
The following table shows the performance of the speckle noise reduction filters which has been compared using quality evaluation metrics such as MAE, PSNR and PCC.

<table>
<thead>
<tr>
<th>Filter</th>
<th>Evaluation Metrics</th>
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<th></th>
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<tbody>
<tr>
<td></td>
<td>Mean Absolute Error</td>
<td>Peak Signal to Noise ratio (Decibel)</td>
<td>Pearson Correlation Coefficient</td>
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<td>Median</td>
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<tr>
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<tr>
<td>Homomorphic Wavelet</td>
<td>0.1068</td>
<td>31.3758</td>
<td>2.2043 e+004</td>
</tr>
</tbody>
</table>

Table 1: Performance analysis of speckle noise reduction filters

**CONCLUSION**

In this paper speckle noise reduction in ultrasound thyroid images using various filters such as Median, Fourier, Wavelet, Homomorphic, Homomorphic wavelet filter is done to increase the quality of the image for further segmentation and classification. The performance of the filters were compared using evaluation metrics such as Mean Absolute Error (MAE), Peak Signal to Noise Ratio (PSNR) and Pearson Correlation Coefficient (PCC).

**REFERENCE**


