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Comparative Analysis Of Speckle Reduction Techniques In Ultrasound Images

Mrs. J. Caroline
Assistant Professor, Information Technology Department
Bishop Caldwell College, Maravanmadam

Abstract

This work provides the knowledge about different filtering techniques such as Mean Filter, Median Filter, Weiner Filter, Min Filter, Max Filter, Lee Filter, Frost Filter, Kuan Filter, Homogenous Filter, Pixel value Filter for speckle noise removal from speckle noise corrupted ultrasound images is discussed. For the evaluation of the performance of above mentioned filters object metrics are calculated. These object metrics are used to calculate the image quality of the output image obtained from above mentioned filters, based on the values of these object metrics the performance of the filters in terms of speckle removal is discussed. Hence the proposed algorithms relieves the human from taking the decision regarding which filter is to be used for an image type since this algorithm compares the different filter outputs and displays the optimal results among the different results produced by different filtering techniques.

***Keywords**: Ultrasound image, Speckle noise, Mean Filter, Median Filter, Weiner Filter, Min Filter, Max Filter, Midpoint Filter, Lee Filter, Frost Filter, Kuan Filter, Homogenous Filter, Pixel value Filter, Average Difference, Mean Square Error, Normalized Absolute Error, Normalized Cross-Correlation, Peak Signal to Noise Ratio, Structural Content, Maximum Difference.*

1. Introduction

Speckle noise arises from coherent summation of the signals scattered randomly within each pixel. Speckle noise is a granular noise that inherently exists in and degrades the quality of the ultrasound and SAR images. Speckle noise occur randomly at all light levels and exposure times and usually due to random error.

Ultrasound is a noninvasive imaging technique. The ultrasound image is a display showing the location of reflecting structures in the horizontal direction as determined by the position of the beam within the body. Ultrasound images are used for assessing activation of the lateral abdominal muscles. It displays the movement and actual function of the body's organs and blood vessels. It is very essential to reduce the noise level and improve the visual quality of an ultrasound image because it is widely used and the ability to visualize moving anatomy in real-time. Ultrasound images provide very useful information in a variety of clinical conditions and safe medical diagnostic technique. This work is carried out to study the speckle characteristics through its mathematical model and then to analyze some prominent speckle reduction filters specific to ultrasound images.

2. Problem Description

An image is produced by image sensor are generally contaminated by noise.

The region of interest in the image

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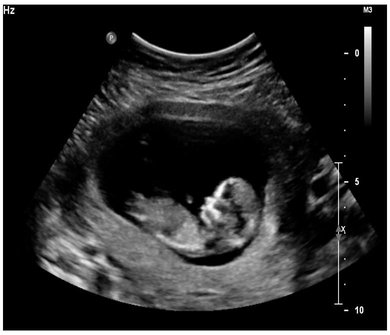
Vol-22- Issue-14-December-2019

can be degraded by the impact of imperfect instrument, the problem with data acquisition process and interfering natural phenomena. Therefore the original image may not be suitable for applying image processing techniques and analysis. Thus image enhancement technique is often necessary and should be taken as the first and foremost step before image is processed and analyzed. An efficient filtering method is necessary for removing noise in the images. The noise removal in the image is still a challenging problem for researcher because noise removal introduces artifacts and causes blurring of the image. Noise modeling in images is affected by capturing instrument, data transmission media, image quantization and discrete source of radiation. There is no unique technique for image enhancement. Different algorithms are used depending on the noise model. Gaussian noise (Random additive) is observed in natural images, speckle noise is observed in ultrasound images.

2.1 Ultrasound Image

Ultrasonic sensors generate high frequency sound waves and evaluate echo which is received back by the sensor called transceiver. The high frequency sound waves are transmitted into the body and involves exposure of the body to a form of radiation and not been shown to be carcinogenic. A method of diagnosing illness and viewing internal body structures in which sound waves of high frequency are bounced off internal organs and tissues from outside the body. Humans are not able to hear ultrasound, though some animals can hear them. Sounds with frequencies above 20,000 hertz are called ultrasounds. Ultrasound images are captured in real-time and it can show the structure and movement of the body's internal organs, as well as blood flowing through blood vessels.[20] Frequency ranges used in medical ultrasound imaging are 2 - 15 MHz [21].



1(a)

Figure 1(a) Ultrasound Image

2.2 Speckle Noise

The appearance of speckle noise is inherent to all coherent imaging systems. Speckle arises from random interference of all backscatter signals within one imaging resolution cell. It is a granular noise that inherently exists in and degrades the quality of the ultrasound, active radar and synthetic aperture radar (SAR) images.

Ultrasound images are masked by multiplicative speckle noise caused by random interference between coherent backscattered waves. Speckle noise is a form of multiplicative noise corrupts medical Ultrasounds imaging making visual observation difficult. [19]

2.2.1 Model of the speckle noise

Speckle is modeled as a signal dependent noise, which tends to reduce the image resolution and contrast, thereby

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Vol-22- Issue-14-December-2019

reducing the diagnostic values of the ultrasound imaging modality. [16]

The speckle noise is known to have a Rayleigh distribution. However, the displayed images from the ultrasound device have different properties. One property of the image is the logarithmic compression. It shows that the linear relationship between the mean and the standard deviation valid for Rayleigh distributed speckle no longer holds for ultrasound images [5].

Speckle noise model is a multiplicative noise it can be modeled as shown in the equation (2.1)

$$J = I + n*I \tag{2.1}$$

where n is uniformly distributed random noise with mean 0 and variance V varying from 0.05 to 0.25.

2.2.2 Need for despeckling

In ultrasound image speckle is a dominant source of noise and should be filtered without affecting important image features. The main purposes for speckle reduction in medical ultrasound imaging are:

1. It makes an ultrasound image cleaner with clearer boundaries.
2. It improves the speed and accuracy of automatic and semiautomatic segmentation & registration.

3.Proposed Methodology

The fundamental requirements of noise filtering methods for medical images are safeguarding important information of the object boundaries and detailed structures, ability to efficiently remove noise in the homogeneous regions and the ability to enhance morphological definitions by sharpening discontinuities.

The filters in the Noise Reduction class are designed to remove extreme or outlier values from image areas that should have relatively uniform values. These outlier values are often the result of additive "noise" imposed on the image by the acquisition system or later processing errors.

A study is made on the spatial filtering techniques are used to remove the speckle noise and to select best filter for a given image on the basis of statistical parameters.

Spatial filters are performed directly on the pixels of an image such as Mean Filter, Median Filter, Weiner Filter, Min Filter, Max Filter, Lee Filter, Frost Filter, Kuan Filter, Homogenous Filter, Pixel value Filter

3.1 Mean/Average filter

Mean filtering is most commonly used as a simple method for reducing noise in an image. The Average (mean) filter smooth image data, thus eliminating noise. This filter performs spatial filtering on each individual pixel in an image using the grey level values in a square or rectangular window surrounding each pixel.

Average filter method is also called neighborhood average method. The essential idea of this method is to replace grayscale value of the centre pixel by average value of neighborhood pixel grayscale. [13]

ISSN:0971-1260

Vol-22- Issue-14-December-2019

$$g(i,j) = \frac{1}{M}\sum f(i,j) + \frac{1}{M}\sum m(i,j) \quad (2.1)$$

$g(i,j)$ = denoised image

M = total points of neighborhood

$f(i,j)$ = noisy image

$m(i,j)$ = mean

3.2 Median filter

The median filter is a non-linear digital filtering technique, frequently used to remove noise from images. It is mostly useful to reduce speckle noise and salt and pepper noise. Its edge-preserving nature makes it practical in cases where edge blurring is undesirable. **[13]** The median filter removes pulse or spike noise by replacing the middle pixel value in the window with the median value of its neighbors in the window. **[16]**

The median filter allows a great deal of high spatial frequency detail to pass while remaining very effective at removing noise on images where less than half of the pixels in a smoothing neighborhood have been effected.

$$g(i,j) = \frac{1}{M}\sum f(i,j) + \frac{1}{M}\sum n(i,j) (2.2)$$

$g(i,j)$ = denoised image

M = total points of neighborhood

$f(i,j)$= noisy image

$n(i,j)$= median

3.3 Wiener Filter

The Wiener filter filters out noise that has corrupted a signal. It is based on a statistical approach. Its purpose is to reduce the amount of noise present in a signal by comparison with an estimation of the desired noiseless signal. The principle of the Wiener filter is defined as an operator that minimizes a mean square error (MSE) between a restored signal and the original signal. It is averaged in respect to both the original signal and noise. **[13]**

Wiener filter (a type of linear filter) is applied to an image *adaptively*, tailoring itself to the local image variance. Where the variance is large, Wiener filter performs little smoothing. Where the variance is small, Wiener performs more smoothing. **[29]**

$$w(i,j) = \sum f(i,j) + (\alpha^2 \sigma^2) \quad (2.3)$$

$w(i,j)$ = denoised image

$f(i,j)$= noisy image

α^2 = mean

σ^2 = median

3.4 Min Filter

The min filter plays a significant role in image processing and vision. It is equivalent to mathematical morphological operation: erosion. It recognizes the darkest pixels gray value and retains it by

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Vol-22- Issue-14-December-2019

performing min operation. This filter was proposed for removing the salt noise from the image by researchers. Salt noise has very high values in images. It removes noise better than max filter but it removed some white points around the border of the region of the interest. In this filter each output pixel value can be calculated by selecting minimum gray level value of the chosen classical window.

$$g(i,j) = \frac{1}{M} mi(i,j) + \sum f(i,j) \quad (2.3)$$

$g(i,j)$ = denoised image

$f(i,j)$= noisy image

s = total points of neighborhood

3.5 Max Filter

The max filter plays a key role in low level image processing and vision. It is identical to the mathematical morphological operation: dilation. The brightest pixel gray level values are identified by this filter. It has been applied by many researchers to remove pepper noise. Though it removes the pepper noise it also removes the block pixel in the border. This filter has not yet applied to remove the speckle in the ultrasound medical image.

It reduces the intensity variation between adjacent pixels. Implementation of this method for smoothing images is easy and also reducing the amount of intensity variation between one pixel and the next.

$$g(i,j) = \frac{1}{M} ma(i,j) + \sum f(i,j) \quad (2.4)$$

$g(i,j)$ = denoised image

$f(i,j)$= noisy image

s = total points of neighborhood

3.6 Lee filter

The lee filter is basically used for speckle noise reduction. It is based on the assumption that the mean and variance of the pixel of the interest is equal to the local mean and variance of all pixels within the moving kernel. **[29]** It uses a least-squares approach to estimate the true signal strength of the center cell in the filter window from the measured value in that cell, the local mean brightness of all cells in the window, and a gain factor is calculated from the local variance and the noise standard deviation. The filter assumes a Gaussian (normal) distribution for the noise values, and calculates the local noise standard deviation for each filter window. The calculation produces an output value close to the local mean for uniform areas, and a value close to the original input value in higher contrast regions. **[18]**

Lee filters are more affective in uniform areas and can maintain edges and other fine detail. It has no user-defined parameters. It is based on the approach where smoothing is performed when the variance over an area is low or constant,

ISSN:0971-1260

Vol-22- Issue-14-December-2019

otherwise, that is, if the variance is high (e.g. near edges), smoothing will not be performed. If there is no smoothing, the filter will output only the mean intensity value [28].

$$L(i, j) = \frac{\alpha + (K(f(i, j) - \alpha)}{K + (\alpha^2 / ENL)} \quad (2.5)$$

$L(i, j)$ = denoised image

$f(i, j)$= noisy image

α = mean

σ = median

$$ENL = \frac{\alpha^2}{\sigma^2} \quad (2.6)$$

$$K = \frac{ENL * \sigma^2 - \alpha^2}{ENL + 1} \quad (2.7)$$

3.7 Frost Filter

The Frost filter is an adaptive filter that incorporates the local image statistics in the filtering process, assuming a negative exponential distribution for the speckle noise. It performs a weighted average of the cell values in the filter window, with the weights for each cell being determined from the local statistics to minimize the mean square error of the signal estimate. The filter weight for a cell is a negative exponential function of the noise standard deviation (calculated locally for each filter window), and also decrease with distance from the center cell. The center cells are weighted more heavily as the variance in the filter window increases. The filter therefore smoothes more in homogeneous areas, but provides a signal estimate closer to the observed value of the center cell in heterogeneous areas. It has no user-defined parameters. **[18]**

$$f(i, j) = \sum \sum c_{i,j} \alpha_{i,j} \quad (2.8)$$

$f(i, j)$ = denoised image

$c_{i,j}$ = central pixel value

$\alpha_{i,j}$ = mean value

3.8 Kaun Filter

The Kaun Adaptive Noise Smoothing filter uses a minimum mean square error calculation to estimate the value of the true signal for the center cell in the filter window from the local statistics. It is similar in approach to the Lee filter, but makes simplifying assumptions in the calculations. The Adaptive Noise Filter calculates the signal estimate from the local mean and variance, and the noise standard deviation (assumed to be constant for the entire image). Kaun filter has no user defined parameters. [28]

Kaun and Lee filter have the same formulation although signal model assumption and derivations are different. It achieves a balance between straight forward averaging in homogeneous regions and identity filter where edges and point features exist. This balance depends on the

ISSN:0971-1260

Vol-22- Issue-14-December-2019

coefficient of variation inside the moving window.

$$K(i,j) = \frac{\alpha + (K(f(i,j)) - \alpha)}{K + (\alpha^2 + K)/ENL} \qquad (2.9)$$

$K(i,j)$ = denoised image

$f(i,j)$= noisy image

α = mean

σ = median

3.9 Homogeneous Filter

Homogeneous filtering is applicable to images corrupted by multiplicative noise. The Homogeneous filtering is based on an estimation of the most homogenous neighborhood around each image pixel. The filter takes into consideration only pixels that belong in the processed neighborhood pixel and leave the edges. To define homogeneous user has to select some area from the image. The contrast changes affect the images by a scaling of the gray values. The filter response directly depends on the scale of the input gray values. If there are large gray values, or large gray value changes, the filter response gets also strong, regardless whether the shape or structure of the neighborhood is of interest or not. A possible way out would be a local normalization of the filter response or a preprocessing of the input images. As the local maxima of the filter response serve as detection hypotheses a gray scale change will not affect the detection results if the filter is homogeneous.

$$H(i,j) = \frac{\alpha * f(i,j)}{\sum \alpha} \qquad (2.9)$$

$H(i,j)$ = denoised image

$f(i,j)$= noisy image

α = mean

3.10 Pixel Value Filter

The pixel value filter used to remove speckle noise in ultrasound image. This filter used the neighborhood pixel value. Sum of Maximum and Minimum neighborhood pixel value used to remove the speckle noise from the ultrasound image.

This filter is different from the midpoint filter. Midpoint filter used pixel value of the image. But pixel value filter used neighborhood pixel value. In this filter each output pixel value can be calculated by selecting minimum and maximum gray level value of the chosen classical window.

$$g(i,j) = \sum mi(i,j) + \sum ma(i,j) \qquad (2.10)$$

$mi(i,j)$ = min value of neighborhood pixel

$ma(i,j)$ = max value of neighborhood pixel

4. Results and discussion

4. 1 Filtering image result

The results are given for the denoised ultrasound image with speckle noise variance 0.05 using Mean Filter, Median Filter, Weiner Filter, Min Filter, Max Filter, Lee Filter, Frost Filter, Kuan

ISSN:0971-1260

Vol-22- Issue-14-December-2019

Filter, Homogenous Filter, Pixel value Filter.

 

(a) (b)

 

(c) (d)

 

(e) (f)

 

(g) (h)

 

(i) (j)

(k)

Figure (a) Noisy image (b) Mean Filter (c) Median Filter (d) Weiner Filter (e) Min Filter (f) Max Filter (g) Lee Filter (h) Frost Filter (i) Kaun Filter (j) Homogenous Filter (k) Pixel Value Filter

4.2 Image Quality Measurement

Image quality is a characteristic of an image that measures the quality of the denoised image, compared to the noise free image. Imaging systems may introduce some amounts of distortion or artifacts in the signal, so the quality assessment is an important problem.

ISSN:0971-1260

Vol-22- Issue-14-December-2019

Table 4.1 Quality Measurement of the denoised image

Performance Metrics	Mathematical Expression
Average Difference	$AD = \frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N}\left\|(X_{j,k} - X'_{j,k})\right\|$
Mean Square Error	$MSE = \frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N}(X_{j,k} - X'_{j,k})^2$
Normalized Absolute Error	$NAE = \frac{\sum_{j=1}^{M}\sum_{k=1}^{N}\left\|(X_{j,k} - X'_{j,k})\right\|}{\sum_{j=1}^{M}\sum_{k=1}^{N}X_{j,k}}$
Normalized Cross-Correlation	$NCC = \frac{\sum_{j=1}^{M}\sum_{k=1}^{N}(X_{j,k} - X'_{j,k})}{\sum_{j=1}^{M}\sum_{k=1}^{N}X^2_{j,k}}$
Peak Signal to Noise Ratio	$PSNR = 10\log_{10}\frac{255^2}{MSE}$
Structural Content	$SC = \frac{\sum_{j=1}^{M}\sum_{k=1}^{N}X_{j,k}^2}{\sum_{j=1}^{M}\sum_{k=1}^{N}X'^2_{j,k}}$
Maximum Difference	$MD = Max\left\|(X_{j,k} - X'_{j,k})\right\|$

ISSN:0971-1260

Vol-22- Issue-14-December-2019

4.3 Results for image quality measurement

Table 4.2 shows the object metrics result of the noise variance is 0.05

Filter	AD	MSE	NAE	NCC	PSNR	SC	MD
Lee Filter	5.0653e-006	1.2546e-006	0.2477	0.9315	107.1459	1.0735	0.2477
Frost Filter	5.0653e-006	1.2546e-006	0.2477	0.9315	107.1459	1.0735	0.2477
Kaun Filter	5.0653e-006	1.2546e-006	0.2477	0.9315	107.1459	1.0735	0.2477
Homogeneous Filter	1.9704e-006	1.8984e-007	0.0963	1	105.3470	1	0.0963
Mean Filter	2.0316e-005	2.0181e-005	0.9934	1.0385	95.0814	0.9629	0.9934
Median Filter	2.0291e-005	2.0133e-005	0.9922	1.2958	95.0918	0.7717	0.9922
Pixel value Filter	2.1231e-005	2.2040e-005	1.0381	3.3145	94.6987	0.3017	1.0381
Min Filter	2.4759e-005	2.9974e-005	1.2106	3.7870	93.3634	0.2641	1.2106
Max Filter	2.4759e-005	2.9974e-005	1.2106	3.7870	93.3634	0.2641	1.2106
Weiner Filter	2.7736e-005	3.7615e-005	1.3562	3.9311	92.3772	0.2544	1.3562

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Vol-22- Issue-14-December-2019

From the table it is found that the Lee, Frost, Kuan Filters are produce better PSNR, AD, SC values and minimal MSE, NAE,NCC, MD values compared in the comparative study.

So the proposed comparative study on despeckling algorithms suggest Lee, Frost, and Kuan Filters for despeckling application over the filters used in the comparative study.

CONCLUSION

In the Digital Image Processing, filtering techniques are used to improve the image quality. The thesis discussed the comparative analysis of speckle reduction techniques in ultrasound images. Lee, Frost, Kuan Filters are found to produce better result than the other filters used in the comparative study. Different image quality metrics such as Average Difference, Mean Square Error, Normalized Absolute Error, Normalized Cross-Correlation, Peak Signal to Noise Ratio, Structural Content, Maximum Difference, are used to compare the image quality.

SCOPE FOR FUTURE WORK

In future a better filter can select by applying fuzzy rules after studying and using the image properties. Metrics like edges in the image, neural network can also be implemented to increase the filter optimization.

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Vol-22- Issue-14-December-2019

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Vol-22- Issue-14-December-2019

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