# A View on Despeckling in Ultrasound Imaging

S.Kalaivani Narayanan and R.S.D.Wahidabanu
*Dhanalakshmi Srinivasan Engineering College,*
*Government College of Engineering Perambalur, Salem,*
*Tamil Nadu, India*
*s_kalai@rediffmail.com, drwahidabanu@gmail.com*

***Abstract***

*Ultrasound imaging is a widely used and safe medical diagnostic technique, due to its noninvasive nature, low cost and capability of forming real time imaging. However the usefulness of ultrasound imaging is degraded by the presence of signal dependant noise known as speckle. The speckle pattern depends on the structure of the image tissue and various imaging parameters. There are two main purposes for speckle reduction in medical ultrasound imaging (1) to improve the human interpretation of ultrasound images (2) despeckling is the preprocessing step for many ultrasound image processing tasks such as segmentation and registration. A number of methods have been proposed for speckle reduction in ultrasound imaging. While incorporating speckle reduction techniques as an aid for visual diagnosis, it has to keep in mind that certain speckle contains diagnostic information and should be retained. The objective of this paper is to give an overview about types of speckle reduction techniques in ultrasound imaging*

## 1. Importance of ultrasound Imaging

ULTRASOUND imaging application in medicine and other fields is enormous. It has several advantages over other medical imaging modalities. The use of ultrasound in diagnosis is well established because of its noninvasive nature, low cost, capability of forming real time imaging and continuing improvement in image quality. It is estimated that one out of every four medical diagnostic image studies in the world involves ultrasonic techniques. US waves are characterized by frequency above 20 KHz which is the upper limit of human hearing. In medical US applications, frequencies are used between 500 KHz and 30 MHz B-mode imaging is the most used modality in medical US. An US transducer which is placed onto the patient's skin over the imaged region sends an US pulse which travels along a beam into the tissue. Due to interfaces some of the US energy is reflected back to the transducer which converts it into echo signals. These signals are then sent into amplifiers and signal processing circuits in the imaging machine's hardware to form a 2-D image. This process of sending pulses launched in different directions is repeated in order to examine the whole region in the body. Thus, US imaging involves signals which are obtained by coherent summation of echo signals from scatterers in the tissue.

In many cases volume quantification is important in assessing the progression of diseases and tracking progression of response to treatment. Thus, 3D ultrasound imaging has drawn great attention in recent years.

## 2. Ultrasound Imaging System

Figure 1 shows a functional block diagram of an ultrasound imaging system. The construction of ultrasound B-mode image involves capturing the echo signal returned from tissue at the surface of piezoelectric crystal transducers. These transducers convert the ultrasonic RF mechanical wave into electrical signal. Convex ultrasound probes collect the echo from tissue in a radial form. Each group of transducers is simultaneously activated to look at a certain spatial direction from which they generate a raw line signal (stick) to be used later for raster image construction. These sticks are then demodulated and logarithmically compressed to reduce their dynamic range to suit the commercial display devices. The final Cartesian image is constructed from the sampled sticks in a process called scan conversion.

Speckle reduction techniques can be applied on envelope detected data, log compressed data or on scan converted data. However, slightly different results will be produced for each data. In the compression stage some useful information about the imaged object may be deteriorated or even lost. However, any processing which works with envelope detected data has more information at its disposal and preserves more useful information. Compared to processing the scan converted image, envelope detected data has fewer pixels and thus incurs lower computational cost.

For optimum result envelope detected data processing is preferred because some information that lost after the compression stage cannot be recovered by working with log compressed data or the scan converted image. However, the real time speckle reduction methods are applied on the scan converted image, since the scan converted image is always accessible where most commercial ultrasound systems do not output the envelope detected or log compressed data.

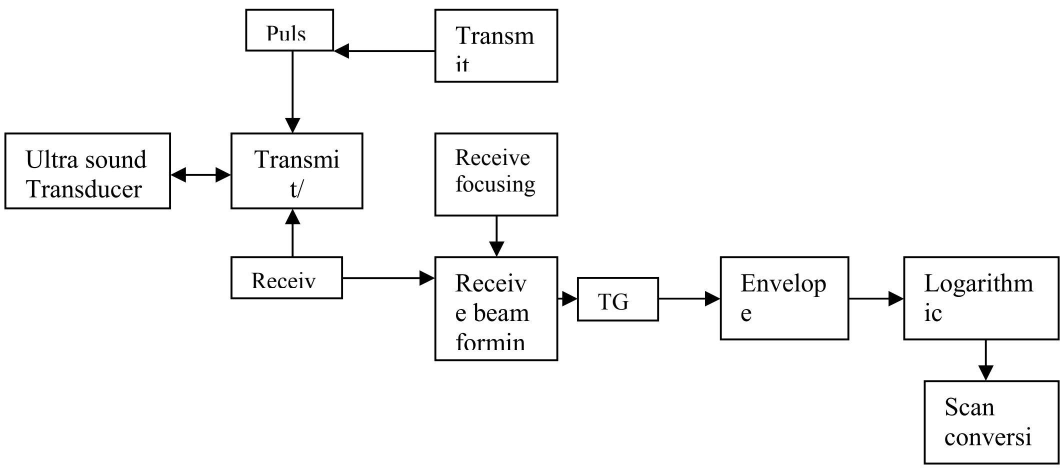


Figure 1. Block diagram of Ultrasound Imaging System

## 3. Speckle in Ultrasound Imaging

Speckle in US B-scans is seen as a granular structure which is caused by the constructive and destructive coherent interferences of back scattered echoes from the scatterers that are typically much smaller than the spatial resolution of medical ultrasound system. This phenomenon is common to laser, sonar and synthetic aperture radar imagery (SAR). Speckle pattern is a form of multiplicative noise and it depends on the structure of imaged tissue and various imaging parameters.

Speckle degrades the target delectability in B-scan images and reduces the contrast, resolutions which affect the human ability to identify normal and pathological tissue. It also degrades the speed and accuracy of ultrasound image processing tasks such as segmentation and registration.

The nature of the speckle pattern can be categorized into one of three classes according to the number of scatterers per resolution cell or the so called scatterer number density (SND), spatial distribution and the characteristics of the imaging system itself. These classes are described as follows:

1. FFS (Fully formed speckle) pattern, which occurs when many fine randomly distributed scattering sites exist within the resolution cell of the pulse-echo system. In this case, the amplitude of the backscattered signal can be modeled as a Rayleigh distributed random variable with a constant SNR of 1.92. Under such conditions, the textural features of the speckle pattern represent a multivariate signature of the imaging instrument and its point spread function. Blood cells are typical examples of this type of scatterers.
2. Non randomly distributed with long-range order (NRLR). Examples of this type are the lobules in liver parenchyma. It contributes a coherent or specular backscattered intensity that is in itself spatially varying. Due to the correlation between scatterers, the effective number of scatterers is finite. This situation can be modeled by the K-distribution. This type is associated with SNR below 1.92. It can also be modeled by the Nakagami distribution.
3. Non randomly distributed with short-range order (NRSR). Examples of this type include organ surfaces and blood vessels. When a spatially invariant coherent structure is present within the random scatterer region, the probability density function (PDF) of the backscattered signals becomes close to the Rician distribution. This class is associated with SNR above 1.92

## 4. Need for despeckling

Thus, speckle is considered as the dominant source of noise in ultrasound imaging and should be processed without affecting important image features.The main purposes for speckle reduction in medical ultrasound imaging are:

1. To improve the human interpretation of ultrasound images – speckle reduction makes an ultrasound image cleaner with clearer boundaries.
2. Despeckling is a preprocess step for many ultrasound image processing tasks such as segmentation and registration – speckle reduction improves the speed and accuracy of automatic and semiautomatic segmentation & registration.

## 5. Key issues in developing an efficient and robust denoising method

One has to take into account the following factors in developing an efficient and robust denoising method for ultrasound images

### 5.1. Adaptation to features of interest

For an experienced radiologist speckle noise (Also referred as *"texture"* in medical literature) may present diagnostic information. The degree of speckle smoothing depends on the expert's knowledge & the application at hand like enhancement for visual inspection or preprocessing for automatic segmentation

For automatic segmentation it is usually preferred to keep the sharpness of the boundaries between different image regions and to smooth out the speckle texture. For visual interpretation the texture smoothing may be less preferable.

### 5.2. Adaptation to spatial content

The medical ultrasound images have significant spatial correlation. A spatially adoptive denoising can be based on statistical content models or on adopting certain filter parameters based on measurements from a local window around each pixel

### 5.3. Proposal of noise models

The basic assumption in majority of speckle filters is that the speckle is fully developed and is modeled as multiplicative noise. Logarithmic operation transforms speckle into additive white Gaussian Noise.

But for different reasons such a speckle model seems to be too simplistic in the case of medical ultrasound images. Speckle is not necessarily fully developed and there exists a pronounced spatial correlation. Moreover the ultrasound devices themselves usually perform a preprocessing of the raw data including even logarithmic compression. Thus in the displayed medical ultrasound images the noise differs significantly from often assumed multiplicative method.

## 6. Speckle reduction methods

Several techniques have been proposed for despeckling in medical ultrasound imaging. In this section we present the classification and theoretical overview of existing despeckling techniques

### 6.1. Compounding Methods

Number of papers have been proposed based on compounding technique [1]-[3].In this method a series of ultrasound images of the same target are acquired from different scan directions and with different transducer frequencies or under different strains. Then the images are averaged to form a composite image.

The compounding method can improve the target detectability but they suffer from degrade spatial resolution and increased system complexity.

### 6.2. Post Acquisition Methods

This method do not require many hardware modification .The post acquisition image processing technique falls under two categories (1) Single scale spatial filtering (2) Multiscale Methods

#### 6.2.1. Single scale spatial filtering Methods

- A speckle reduction filter that changes the amount of smoothing according to the ratio of local variance to local mean was developed [4].in that method smoothing is increased in homogeneous region where speckle is fully developed and reduced or even avoided in other regions to preserve details

- An unsharp masking filter was suggested [5] in which the smoothing level is adjusted depending on the statistics of log compressed images

The above mentioned filters have difficulty in removing speckle near or on image edges

- Recently proposed filter utilizing short line segments in different angular orientations and selecting the orientation that is most likely to represent a line in the image [6]

This technique poses a tradeoff between effective line enhancement and speckle reduction

- Numbers of Region growing based spatial filtering methods [7-9] have been proposed .In these methods it is assumed that pixels that have similar gray level and connectivity are related and likely to belong to the same object or region. After all pixels are allocated to different groups, spatial filtering is performed based on the local statistics of adaptive regions whose sizes and shapes are determined by the information content of the image.

The main difficulty in applying region growing based methods is how to design appropriate similarity criteria for region growing. Different types of filters are used in the application of despeckling in ultrasound imaging. The most commonly used types of filters are:

a. ***Kaun &Lee Filters*** *[10]* - Lee filter 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.Kaun and Lee filter have the same formulation although signal model assumption and derivations are different. These two filters achieve a balance between straight forward averaging in homogeneous regions and identity filter where edges and point features exist. This balance depends on the coefficient of variation inside the moving window.

b. ***Frost Filter*** *[11]* achieves a balance between averaging and all pass filter by forming an exponentially shaped filter kernel. The response of the filter varies locally with the coefficient of variation

c. ***Enhanced Lee & Frost filter*** are used to alter the performance locally according to the threshold value. Pure averaging is induced when the local coefficient of variation is below a lower threshold. The filter performs as a strict all pass filters when the local coefficient of variation is above a higher threshold. When the coefficient of variation is in between the two thresholds, a balance between averaging and identity operation is computed.

d. ***Mean Filter*** *[12]* has the property of locally reducing the variance thus reducing SNR and it requires the user to specify only the size of the window. However it has the effect of potentially blurring the image. This filter is optimal for additive Gaussian noise whereas the speckled image obeys a multiplicative model with non Gaussian noise. Therefore simple mean is not the optimal choice.

e. ***Median Filters*** *[13]* are utilized for despeckling due to their robustness against impulsive type noise and edge preserving characteristics. The median filter produces less blurred images. The compounding procedure uses both the mean and median filters.

f. ***Maximum a posterior (MAP)*** *filter* requires assumption about the distribution of the true process and the degradation model. Different assumptions lead to different MAP estimators and different complexities.

g. ***Diffusion filtering :***

Perona and Malik (14) proposed nonlinear partial differential equation for smoothing image on a continuous domain. The diffusion is described by

$$\frac{\partial I}{\partial t} = div[c(\|\nabla I\|).\nabla I], \quad I(t=0) = I_0 \tag{1}$$

Where div is the divergence operator, $\|\nabla I\|$ is the gradient magnitude of the image I, $c(\|\nabla I\|)$ is the diffusion coefficient or the diffusivity function and $I_0$ is the original image. If the function $c(\|\nabla I\|)$ is constant for all image location the diffusivity function $c(\|\nabla I\|)$ is a monotonically decreasing function of the gradient magnitude. In the anisotropic diffusion method the gradient magnitude is used to detect an image edge or boundary a step discontinuity in intensity.

- An edge sensitive diffusion method called speckle reducing anisotropic diffusion (SRAD) has been proposed to suppress speckle while preserving edge information [15]. A tensor based anisotropic diffusion method called non linear coherent diffusion (NCD) used for speckle reduction and coherent enhancement [16].

The above mentioned diffusion methods can preserve or even enhance prominent edges when removing speckle. However the methods have one common limitation in retaining subtle features such as small cysts and lesions in ultrasound images.

- A modified SRAD filter which rely on the Kaun filter rather the Lee filter was developed [17] and this approach is called Detail preserving anisotropic Diffusion (DPAD).This method is combined with matrix anisotropic diffusion method designed to preserve and enhance small vessel structures referred as oriented speckle reducing anisotropic diffusion [18].

**6.2.2 Multi scale Methods**

Several multi scale methods based on wavelet and pyramid have been proposed for speckle reduction in ultrasound imaging.

**1. Wavelet based speckle reduction methods**

The wavelet based speckle reduction method usually include (1) logarithmic transformation (2) wavelet transformation (3) modification of noisy co efficient using shrinkage function (4) invert wavelet transform and (5) exponential transformation. This method can be classified into three groups

1. ***Thresholding methods*** **-** The wavelet coefficients smaller than the predefined threshold are regarded as contributed by noise and then removed [19],[20]. The thresholding techniques have difficulty in determining an appropriate threshold.
2. ***Bayesian estimation methods*** **–** This Method approximates the noise free signal based on the distribution model of noise free signal and that of noise [21]-[23]. Thus, reasonable distribution models are crucial to the successful application of these techniques to medical ultrasound imaging
3. ***Coefficients correlation methods*** **-** This is an undecimated or over complete wavelet domain denoising method which utilizes the correlation of useful wavelet coefficients across scales [24]. However this method does not rely on the exact prior knowledge of the noise distribution and this method is more flexible and robust compared to other wavelet based methods.

**2. Pyramid based speckle reduction methods**

Pyramid transform has also been used for reducing speckle. Approximation and interpolation filters in pyramid transform have low pass properties so that pyramid transform does not require quadrature mirror filters unlike sub band decomposition in wavelet transform

- A ratio laplacian pyramid was introduced by considering the multiplicative nature of speckle [25]. This method extended the conventional Kaun filter to multi scale domain by processing the interscale layers of the ratio laplacian pyramid. But this method differs from the need to estimate the noise variance in each interscale layers.

- A speckle reduction method based on non linear diffusion filtering of band pass ultrasound images in the laplacian pyramid domain has been proposed [26] which effectively suppresses the speckle while preserving edges and detailed features.

## 7. Speckle models

Although the existing despeckling filters are termed as edge and feature preserving filters some major limitation exists

i. The filters are sensitive to the noise components
ii. Noise attenuation is not sufficient especially in the smooth and background areas
iii. The existing filters do not enhance edges but they only inhibit smoothing near edges

Thus, effective despeckling requires an accurate statistical model of ultrasound signals. A generalized model of the speckle imaging can be written as

$$g = fn + m \qquad (2)$$

Let $g$ denote the observed signal, $m, n$ respectively the multiplicative and additive components of noise introduced by the acquisition process and $f$ the original signal without noise.Generally the effect of additive noise is very small compared to multiplicative noise,So the simplified noise model :

$$g = fn \tag{3}$$

The statistics of speckle noise can be categorized into different classes according to number of scatterers per resolution cell called scatterer number density (SND). In the case of many fine randomly distributed scatterers per resolution cell (>10) the speckle can be modeled by a Rayleigh distribution [27] with a SNR of 1.92.When the scatterer densities are smaller a generalized version of Rayleigh distribution called the K-distribution[28] can be used. For high SNR the Rician model [29] can be used for lower the speckle can be modeled using Homodyne K-distribution[30] more analytical models including

## 8. Results from study

Six different single scale spatial filtering methods (ie.,WIENER, MEDIAN, ADOPTIVEMEDIAN, HOMOMORPHIC, LEE AND FROST FILTERS), two diffusion filtering methods (ie., SRAD, PERONA MALIK.) and one multi scale method (BAYES THRESHOLDING) were applied on ultrasound phantom and synthetic2D image with two levels of multiplicative noise(variance $\sigma_n$ =0.5, $\sigma_n$ =0.05). The mean and standard deviation are measured to quantify the results. The synthetic image has been selected from MATLAB library function (*eight.tif).*

### 8.1 Result From Simulation Study

The synthetic image which has been selected from MATLAB library function (>>*eight.tif)* is corrupted by multiplicative noise (speckle) with variance $\sigma_n$ =0.05 using the MATLAB command ( >>imnoise(image,'speckle',0.5)) and various filters have been applied ,mean and standard deviation for filtered images are measured for quantitative analysis. Figure 2 shows the synthetic image, synthetic image with speckle noise of variance ($\sigma_n$ =0.05) and results of various filters. Figure 3 shows the synthetic image, synthetic image with speckle noise of variance ( $\sigma_n$ =0.5) and results of Various filters

Table II shows the mean and standard deviation for the synthetic image and various filtered images with speckle noise 0f $\sigma_n$ =0.5 and $\sigma_n$ =0.05,

### 8.2 Result From Phantom Study

A 2D ultrasound phantom was despeckled using various filter approach and results were shown in the figure.4.The mean and standard deviation of the initial image and the filtered images were produced in Table III

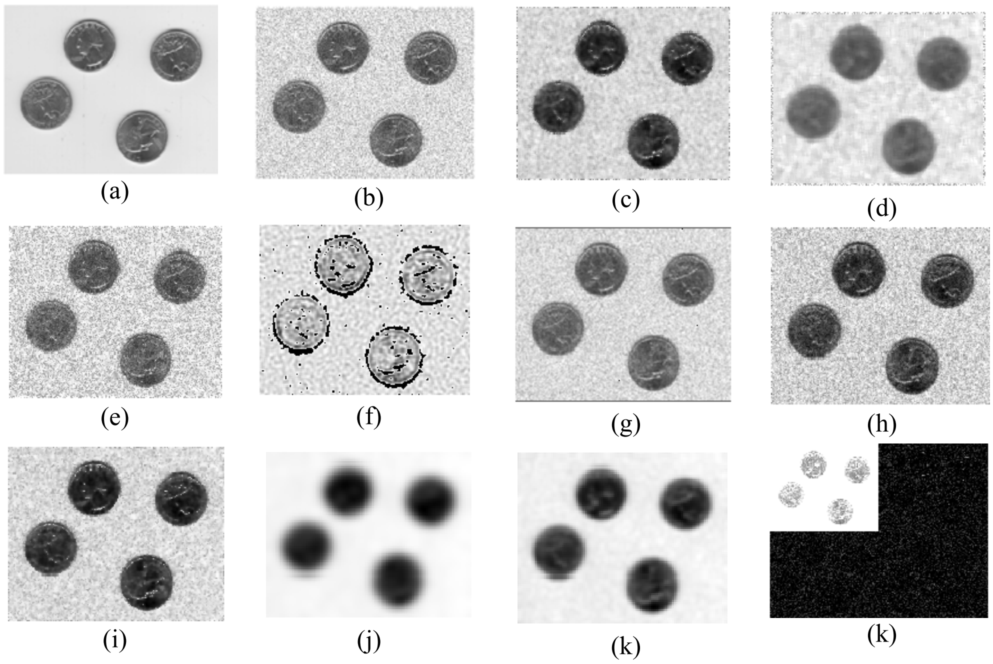


Figure 2. Results of various filters on a multiplicative noise with $\sigma_n$ =0.05: (a) Original image, (b) Noisy Image, (c) Wiener, (d) Median, (e) Adoptive Median, (f) Homomorphic, (g) Lee, (h) Frost, (i) Perona Malik, (j) SRAD with iteration=200, (k) SRAD with iteration=400, (l) Bayes thresholding.

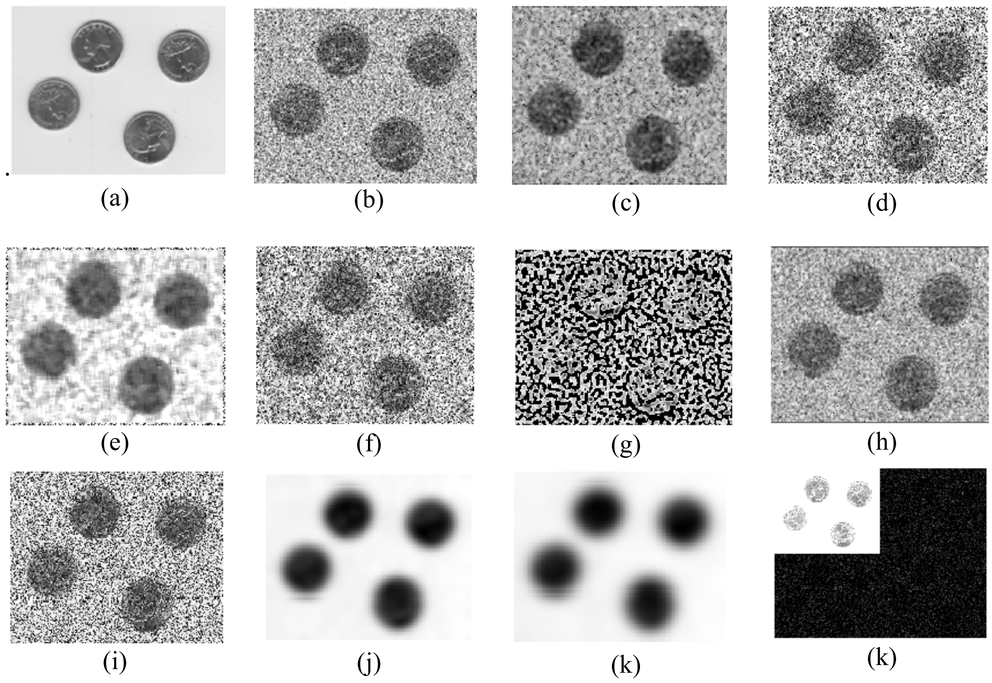


Fig. 3. Results of various filters on a multiplicative noise with $\sigma_n$ =0.5: (a) Original image, (b) Noisy Image, (c) Wiener, (d) Median, (e) Adoptive Median, (f) Homomorphic, (g) Lee, (h) Frost, (i) Perona Malik, (j) SRAD with iteration=200, (k) SRAD with iteration=400, (l) Bayes thresholding.

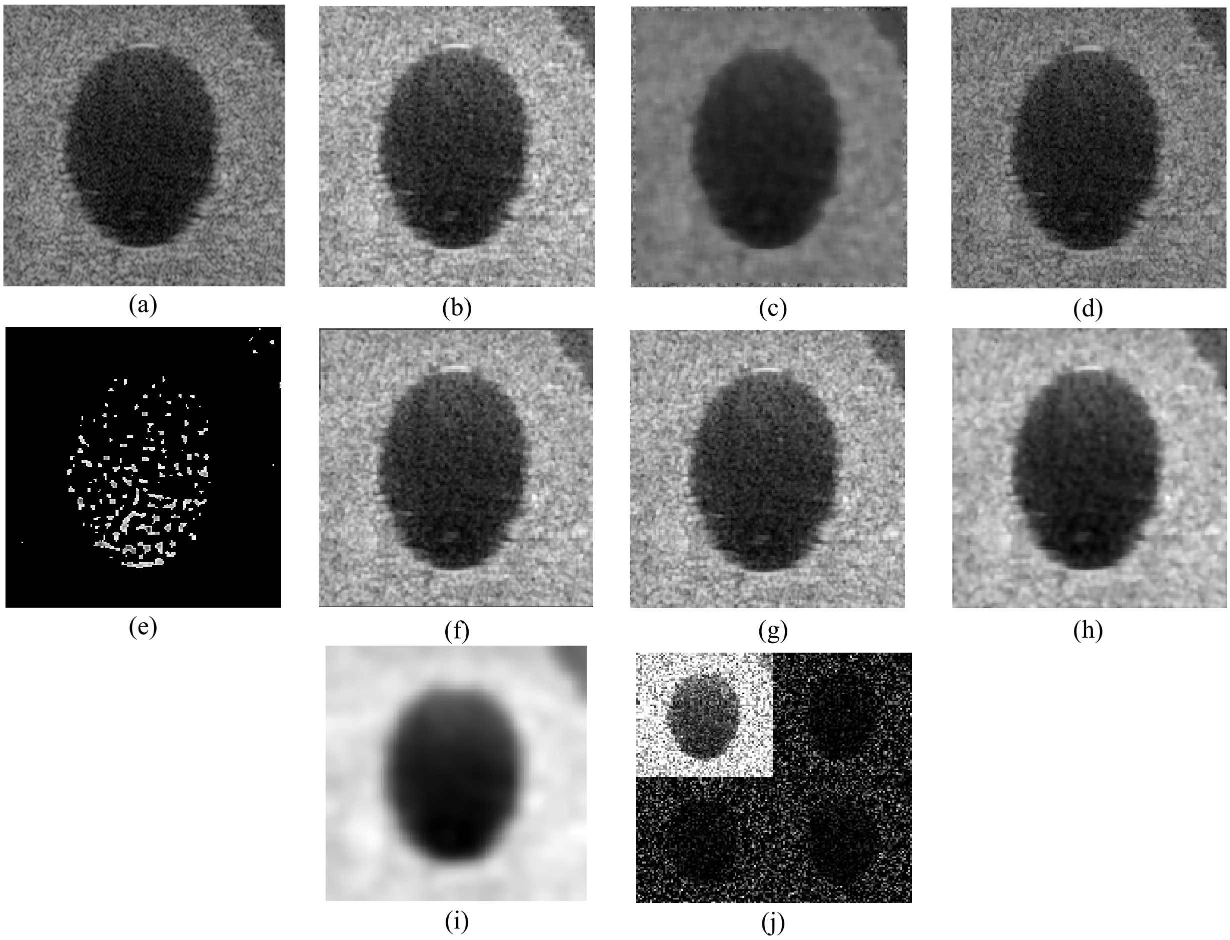


Fig. 4. Results of various filters on 2D ultrasound Phantom: (a) Original image, (b) Wiener, (c) Median, (d) Adoptive Median, (e) Homomorphic, (f) Lee, (g) Frost, (h) Perona Malik, (i) SRAD with iteration=200,(j) Bayes thresholding.

# 9. Filter assessment

Numbers of metrics are used to assess the performance of the filter and other methods. The commonly used criterions are mean and standard deviation. These two metrics were calculated for the initial and filtered images. The results were listed in Table II for simulated image and in Table III for ultrasound phantom.

## 9.1 Performance Measure

To quantify the performance improvements of the speckle reduction method various measures are used. The commonly preferred measures are mean squared error (MSE), universal quality index Q, peak signal to noise ratio (PSNR), Correlation coefficient (CoC), Edge preservation index (EPI), structural similarity index (SSI), Contrast to noise ratio (CNR) and Pratt's figure of merit (FOM).The definition and parameters of measures are listed in Table I.

Figure of Merit is used to compare edge preservation performance of the scheme and the value is unity for ideal edge detection. Structural similarity index and Correlation co efficient are measure of similarity between the original and denoised images, EPI is measure of edge preservation and the value of SSI, COC and EPI is one for good visual quality. The quality index models any distortion as a combination of three factors: loss of correlation, luminance distortion and contrast distortion

Table 1. List of measures

| Measure | Definition | Parameters |
|---|---|---|
| MSE | $\frac{1}{MXN}\sum_{(i,j)=1}^{MXN}(\hat{S}(i,j)-S(i,j))^2$ | S – reference image<br>$\hat{S}$ - filtered images |
| PSNR | $10\log\left(\frac{\sigma_{\hat{S}}^2}{\sigma_{\hat{S}}}\right)$ | $\sigma_{S,}$ – variance of noise free image ,<br>$\sigma_{\hat{S},}$ – variance of unit mean complex Gaussian random field used to<br>produce the speckled image |
| CoC | $\frac{\sum(S-\bar{S})(\hat{S}-\bar{\hat{S}})}{\sqrt{\sum(S-\bar{S})^2\sum(\hat{S}-\bar{\hat{S}})^2}}$ | S, $\hat{S}, \bar{S}$ , $\Delta S$ are original denoised image, mean of S and high pass<br>Filtered S using discrete Laplacian operator. Ci is the constant to<br>avoid instability |
| EPI | $\frac{\sum(\Delta S-\Delta\bar{S})(\Delta\hat{S}-\Delta\bar{\hat{S}})}{\sqrt{\sum(\Delta S-\Delta\bar{S})^2\sum(\Delta\hat{S}-\Delta\bar{\hat{S}})^2}}$ | |
| SSI | $\frac{\left(2\hat{S}\bar{\hat{S}}+C_1\right)(2\sigma_{S\hat{S}}+C_2)}{\left(\bar{S}^2+\bar{\hat{S}}^2+C_1\right)(\sigma_S^2+\sigma_{\hat{S}}^2+C}$ | |

| | | |
|---|---|---|
| Universal Quality Index(Q) | $\frac{4\sigma_{yg}\overline{yg}}{(\sigma_g^2+\sigma_y^2)(\bar{y}^2+\bar{g}^2)}$ | g, y, $(\bar{\cdot})$ and $\sigma_{yg}$ are input, output images, mean intensity and cross correlation |
| CNR | $\frac{\lvert\mu_1-\mu_2\rvert}{\sqrt{\sigma_1^2+\sigma_2^2}}$ | $\mu_1$ , $\sigma_2^2$ are mean and variance of intensities of pixels in a region of<br><br>interest (ROI), $\mu_2$ ,$\sigma_1^2$ are the mean and variance of intensities of pixels in a background region that has the same size as the ROI to be compare with. |
| FOM | $\frac{1}{max\{N,N_{ideal}\}}\sum_{i=1}^{n}\frac{1}{1+d_i^2\alpha}$ | $N,N_{ideal}$ are number of detected, ideal edge pixels, *i d* is Euclidean<br><br>distance between the ith edge pixel and the nearest ideal edge pixel. α<br><br>lies in the range (0,1) and α =1 shows perfect edge detection. |

Table 2. For original image, Mean= 0.7775, Standard deviation= 0.2072

| **Image** | **Speckle noise With $\sigma_n$ =0.05** | | **Speckle noise with $\sigma_n$ =0.5** | |
|---|---|---|---|---|
| | **Mean** | **Standard Deviation** | **Mean** | **Standard Deviation** |
| Noisy Image | 0.7843 | 0.2770 | 0.6744 | 0.3730 |
| Wiener | 0.7621 | 0.2694 | 0.6550 | 0.2488 |
| Median | 0.8170 | 0.2183 | 0.8057 | 0.2406 |
| Adoptive Median | 0.7835 | 0.2324 | 0.6966 | 0.3104 |
| Homomorphic | 0.8259 | 0.2378 | 0.5872 | 0.4323 |
| Lee | 0.7827 | 0.2144 | 0.6744 | 0.3737 |
| Frost | 0.7328 | 0.2614 | 0.7192 | 0.2601 |
| Perona Malik | 0.7417 | 0.2794 | 0.6846 | 0.3323 |
| SRAD.iteration=200 | 0.8331 | 0.2868 | 0.8238 | 0.2834 |
| SRAD.iteration=400 | 0.8223 | 0.2837 | 0.7805 | 0.2818 |
| Bayes Thresholding | 0.5118 | 0.4689 | 0.5108 | 0.4689 |

Table 3. The mean and standard deviation for the ultrasound Phantom image and result of various filters

| Image | Mean | Standard Deviation |
|---|---|---|
| Noisy Image | 0.5942 | 0.2708 |
| Wiener | 0.6177 | 0.2856 |
| Median | 0.4859 | 0.2812 |
| Adoptive Median | 0.4906 | 0.2916 |
| Homomorphic | 0.2174 | 0.4083 |
| Lee | 0.5918 | 0.2811 |
| Frost | 0.5942 | 0.2776 |
| Perona Malik | 0.6154 | 0.2874 |
| SRAD.iteration=200 | 0.7011 | 0.3192 |
| SRAD.iteration=400 | 0.6954 | 0.2984 |
| Bayes Thresholding | 0.4171 | 0.4261 |

## 10. Conclusion

Thus, while developing an efficient and robust denoising method for ultrasound images one has to take into account number of factors. The choice of despeckling filter and speckle model plays an important role in the design of despeckling methods and it differs from application to application. Most commonly preferred models and filters were discussed with its merits and demerits in this paper.

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