International Journal of Advanced Technology in Engineering and Science
Vol. No.5, Issue No. 05, May 2017
www.ijates.com
ijates
ISSN 2348 - 7550

PERFORMANCE COMPARISON OF VARIOUS FILTERS ON DESPECKLING OF MEDICAL ULTRASOUND IMAGING

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ABSTRACT

Ultrasound Imaging plays vital role in diagnoses a disease. US image suffers from speckle noise. Despeckling is an important task for accurate diagnosis. In this paper experiment has been performed to measure the effectiveness of various filters available for despeckling. Results are compared qualitatively and quantitatively the Peak Signal to Noise Ratio and SSIM parameters are used to quantify the results. On basis of these parameters the performance of various filters are shown.

Keywords: *Median Filter, Mean Filter, PSNR, SSIM, Speckle Noise.*

I. INTRODUCTION

Medical imaging is very much useful to investigate the human body to diagnose diseases. Currently in medical imaging technologies, ultrasound imaging is widely used modality, practically safe to human body, non surgical, portable, and lesser cost. US images are accessed by processing the echo signals reverted by body tissues, obtain distinct acoustic impedances. Due to this it can also show the movement of body's internal organ movement as well as the blood flowing through the blood vessels. These features enable ultrasound imaging the most adaptable diagnostic tool around the world in almost all hospitals.

Ultrasound imaging has been considered the finest technique for organ and soft tissue imaging from the last many years. Unfortunately ultrasound imaging gives low quality images that leads it difficult to interpret as they strongly depends on the operator's skill. This constraint is due to presence of speckle noise [1].

Due to US imaging principle it suffers from strong speckle noise. Speckle is image variance or a granular noise, exists inherently and degrades the quality of the medical ultrasound images. Speckle noise is mainly due to the interference of the returning wave at the transducer aperture. Speckle noise consequences from these patterns of constructive and destructive interference shows as bright and dark dots in the image. Speckle noise blurs the image details and decrease the contrast of ultrasound image, thus diminish the trustworthiness of the image that leads to the wrong diagnosis of the diseases. As a result, speckle noise reduction is the foremost requirement, whenever ultrasound imaging is used for tissue characterization.

Our objective is to improve the quality of the images by reducing the effect of speckle noise from the US imaging. For this many algorithm are evolved that are describe in next section. There are several parameters that are used to measure the quality of filtered image like SNR, PSNR, MSE, HVM, Covariance, SSIM, UIQI and many more. Some of these parameters are also used in all below described methods. In this paper we compare the quality of filtered images on the basis of parameters PSNR and SSIM.

II. RELATED WORK

To improve the quality of filtered images several techniques and algorithms have been proposed to filter the speckle noise present in the ultrasound images. These methods focus not only in the filtering of images but also on the quality of the filtered images.and includes single scale to multiscale methods. In single scale method we apply the denoising filters like Wiener and Median filters directly on the original image [2,3,4,5]. Though the implementation of such type of filters are easy but these filters fails to restore the original image and unable to preserve the needful information in the resulting filtered images.

Shrimali et al. discussed a method which used the concept of morphological image processing techniques [6]. This method used a structuring element to model the attributes of the speckle like size and shape.

In the Multiscale methods, single scale methods are applied to several sub-images. These subimages are obtained by using wavelet decomposition. Now a days wavelet transforms are used for recovering signals from noisy ultrasound image [7,8,9].

Abd-Elmoniem et al. proposed a Nonlinear Coherent Diffusion (NCD) filter [10] . NCD performs the transformation of multiplicative speckle signals into an additive Gaussian noise in Log-compressed ultrasound images. Another method proposed by Yu et al. named Speckle reducing anisotropic diffusion (SRAD) technique [11,12] is the extension of the Perona-Malik diffusion model which is a technique whose aim is to reduce image noise without removing considerable parts of the image like edges, lines or other details that are relevant for the analysis of the image. SRAD cast the typical spatial adaptive filers into diffusion model. Oriented SRAD (OSRAD) filter [13] is the improvement of SRAD, is based on matrix anisotropic diffusion and can formulate the different diffusion across to the principal curvature directions. Several methods [14,15,16] are there based on Rayleigh distribution metric for denoising ultrasound images. Unlike other methods, denoising of ultrasound images by nonlocal methods has been done be Guo et al [17]. This method modifies the original nonlocal method by using MAP method of Rayleigh distribution. The performance this method is satisfactory but on the other hand the computation efficiency is very low as large amount of time has been consumed by the algorithm to compute the MAP method of Rayleigh distribution. Deka [18] proposed method, use sparse coding technique to remove speckle noise. This scheme use sparse representations over a learned overcomplete dictionary. The result seems to be satisfactory but the dictionary learning is a time consuming work and increase the time complexity. Wang [19] proposed a variational method for denoising the ultrasound image for edge enhancement and speckle suppression.

As discussed previously there are several parameters that are used to evaluate the image. In this paper we compare the quality of filtered images on the basis of parameters PSNR and SSIM.

III. IMAGE QUALITY METRICS

- The image's quality can be affected due to distortions created by many factors from the time it is being captured and visualize to human observer. This may be during storing, processing, compressing and transmitting. There are two methods, subjective method and objective method are used to evaluate the image quality.
- Subjective method of evaluation is time consuming and expensive; here we have to select the observers, show them a number of images and ask them to rate the quality of images on the basis of their opinion. While in the objective evaluation we use algorithms to evaluate the quality of the image without interference of human being.
- Image quality assessment is used to measure the degradation in the images so that the quality of the resultant image gets improve. For objective evaluation several techniques are defined to develop objective image quality matrices. PSNR, MSE, HVM, SSIM, UIQI are commonly used to measure image quality. Here we compare the two image quality measure: PSNR and SSIM.

i. Peak Signal-to-Noise Ratio (PSNR), Signal–to-noise ratio (SNR) is can be described as a mathematical measure of image quality based on the pixel difference between two images [3]. The SNR evaluation is an estimation of quality of reconstructed image in comparison to the original image and is defined as in (1)

- $$PSNR = 10 log \frac{}{N} \qquad (1)$$

- Where MSE is the Mean Square error is computed by mean of the squared intensity of original image. The resulting image pixels and can be describe as (2)

- $$MSE = \frac{1}{NM} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} (m, \qquad (2)$$

ii. Structural Similarity Index (SSIM) is a technique to measure the similarity between two images. It is considered as a quality measure of one of the images being compared provided the other image is regarded as of perfect quality. Wang et. al[10], suggested Structural Similarity Index as an improvement for Universal image quality index UIQI in which comparison between original and distorted image is based on three components: luminance, contrast, and structural comparison as in Fig.1.

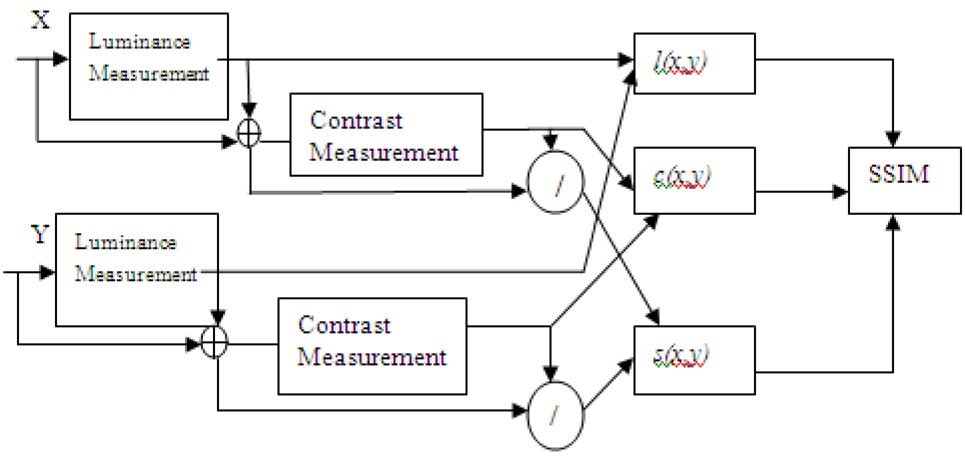

Fig. 1. Structural Similarity Index (SSIM) measurement system

Steps to compute SSIM:

1. Divide the original and noisy images into 8×8 blocks and converted these blocks into vectors.
2. Compute two standard derivations, two means and one covariance value from the images as given by equation (3), (4), and (5).

$$\mu_x = \frac{1}{T}\sum_{i=1}^{T} \qquad \mu_y = \frac{1}{T}\sum_{i=1}^{T} \tag{3}$$

$$\sigma_x^2 = \frac{1}{T-1}\sum_{i=0}^{T}(x_i - \bar{x})^2 \; \sigma_x^2 = \frac{1}{T-1}\sum_{i=0}^{T}(x_i - \tag{4}$$

$$\sigma^2 = \frac{1}{T}\sum_{i=1}^{T}(x - \bar{x})\,(y_i - \tag{5}$$

3. On the basis of statistical values Luminance, contrast, and structure comparisons are computed. SSIM measure between original image (x) and despeckled image(y) is given by equation (6).

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} +}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 +} \tag{6}$$

Where c_1 and c_2 are constants.

IV. METHODOLOGY

Initially we select the images in 8 bpp, and implement the metrics on these images and compare them based on two objective evaluations: PSNR and SSIM. metrics by simulating them using MATLAB-2015a software on Intel core i3 with 3 GB RAM.

Ten different types of US images are selected for observation. The speckle noise with variance 0.01, 0.05 and 0.1 respectively has been introduced in each image. To compare the performance mean filter, median filter are applying on these noisy images. The resulting filtered images have been compared with original image and the parameters PSNR and SSIM have been measured. In this paper the results of only two images are shown.

V. RESULTS

The image quality metrics used here are objective measurement that is based on some predefined mathematical algorithms. Measuring image quantity for the two images gave the results included in Table1 and Table2.

Table 1. Comparison between PSNR and SSIM parameters values for image1

Filters	PSNR			SSIM		
	0.01	0.05	0.1	0.01	0.05	0.1
Mean	24.2923123	23.6403303	22.9741790	0.9078632	0.8788005	0.8496808
Median Filter 3x3	23.3333334	22.5207797	21.7602976	0.9032612	0.8488546	0.7960444
Median Filter 5x5	21.6358293	21.1713106	20.6846945	0.8083313	0.6504458	0.7552753

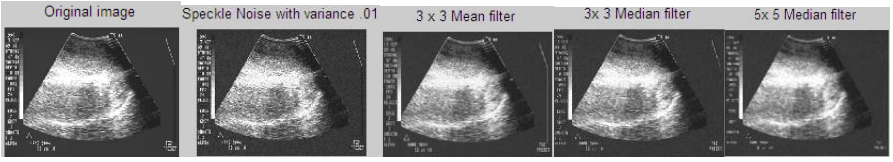

Fig. 2. Effect of filter on Speckle noise with variance 0.01 on image1

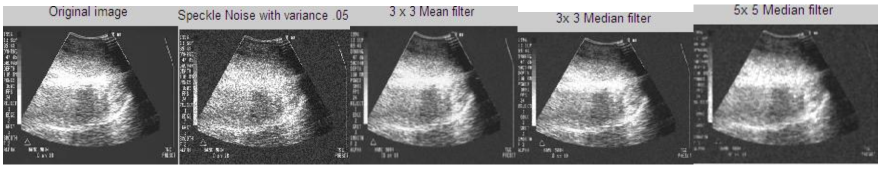

Fig. 3. Effect of filters on Speckle noise with variance 0.05 on image1

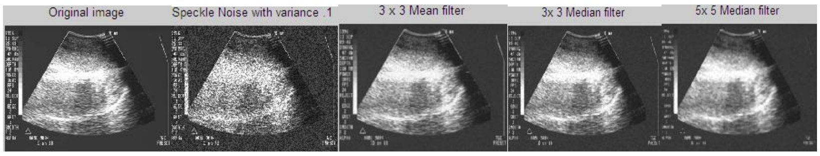

Fig. 4. Effect of filter on Speckle noise with variance 0.1on image1

Filters	PSNR			SSIM		
	0.01	0.05	0.1	0.01	0.05	0.1
Mean Filter 3x3	23.8709296	22.7770830	21.7391609	0.8234327	0.7337966	0.6509414
Median Filter 3x3	23.8863072	22.5341645	20.6887918	0.8091166	0.6440268	0.5292942
Median Filter 5x5	20.9841364	20.5005558	20.9841364	0.6504458	0.5785102	0.6504458

Fig. 5. Effect of filter on Speckle noise with variance 0.01 on image2

Fig. 6. Effect of filter on Speckle noise with variance 0.05 on image2

Fig. 7. Effect of filter on Speckle noise with variance 0.1 on image2

IV. DISCUSSION

It can be observe by experimenting that from Table 1 and Table 2 that for different types of ultrasound images by increasing the speckle noise variance the PSNR value for mean filter gives better result than 3x3 median filter and 5x5 median filter. It means mean filter perform better than other filter also from Table 1 and Table 2 the SSIM value of mean filter is better than other filter which means the mean filter also restore the original image better than other filter. By visual inspection of images shown in figure(2)-(7) the quality of images filtered by mean filter is better than images filtered by other filter. At all noise level. It is clear from the above discussion that mean filter perform well than in despeckling of medical ultrasound images both in terms of noise filtering and restoring the original structure of the images.

V. CONCLUSION AND FUTURE WORK

Experiment has been performed on the sampled ultrasound images shows that mean filter gives better result than median filter by varying the intensity of the speckle noise. This experiment is performed on very basic filtering techniques which can be enhanced by using various types of others filters like bilateral filter, trilateral filter, wavelet based filters, entropy based filters and many more.

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