Comparison of Various Noise Removal Methods for Speckle Reduction in Ultrasound Images

Harpreet Kaur
Master of Technology,
Department of Computer Science, Punjabi University,
Patiala, Punjab, India

ABSTRACT

Ultrasound images have non-invasive nature. So, they are most widely used in medical imaging for medical diagnosis. These images are inexpensive and provide the real time imaging without using radiation. But ultrasound images suffer from speckle noise which degrades the image quality. Low quality images do not provide effective analysis and diagnosis of medical images. Speckle noise in ultrasound images is caused by the interference of the energy from randomly distributed structure scatters. Speckle noise is difficult to remove from the ultrasound images. In this paper, various filters such as median filter, wiener filter, bilateral filter and non-local means filter are applied on different ultrasound images to remove the speckle noise. These filters are compared for their PSNR (Peak Signal-to-Noise Ratio) value, RMSE (Root Mean Square Error) value and computational speed. Experiments show that non-local means filter performs better than the other filters but this method is computationally slow.

Keywords: Ultrasound images, Speckle reduction, Median filter, Wiener filter, Bilateral filter, Non-Local Mean filter, PSNR, RMSE.

1. INTRODUCTION

Digital image processing plays very important role in medical diagnosis. Images of living objects are taken by different technologies like X-ray, Ultrasound, Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) etc. From all these technologies, Ultrasound is used most widely. Medical Ultrasound imaging is done using ultrasonic waves in 3 to 20 MHz range. By using transducers, the ultrasonic waves are produced and these waves travel through body tissues. When a wave hits an object or surface, it reflected back and received by the transducers. Then, the wave changes to the electrical current. The main advantages of ultrasound imaging are that there is no use of radiation, these are inexpensive. Ultrasound imaging has non-invasive nature, these are excellent for cyst (fluid field cavities) and provide the real time imaging. Ultrasound imaging has a serious disadvantage that these are suffered from a noise called speckle. Noise is the undesired information that degrades the image. Noise has many types from which speckle noise is one.

Speckle is a multiplicative noise. Speckle noise in ultrasound is caused by the interference of the energy from randomly distributed structure scatters. The speckle noise degrades the image, limiting the detectabilities of small, low-contrast lesions, thus making the ultrasound images less useful for medical diagnosis [1]. Noise removal or image denoising refers to the recovery of the digital image that has been degraded or distorted by noise. The purpose of image denoising is to estimate the original image from noisy data. By using some denoising techniques, images lose some important information. Also some denoising methods cause blurring and distortion of edges.

2. SPECKLE MODEL

The speckle noise is the noise which gets multiplied with the image [5].

$$g(x,y) = f(x,y) \times h(x,y) \quad (1)$$

Where, $g(x,y)$ is the noisy image, $f(x,y)$ is the actual image, $h(x,y)$ is the degraded function. It follows a Rayleigh Density Probability Distribution [7].

$$p(h,\sigma_h) = \left(\frac{h}{\sigma_h^2}\right).\exp\left(\frac{-h^2}{2\sigma_h^2}\right) \quad (2)$$

$$\mu(h) = \sigma_h\sqrt{\frac{\pi}{2}} \quad (3)$$

$$\sigma(h)^2 = \frac{\sigma_h(4-\pi)}{2} \quad (4)$$

Where, σ_h is the shape parameter, $\mu(h)$ is the mean and $\sigma(h)^2$ is the variance. The real and imaginary parts of h are independent orthogonal, identically distributed Gaussian random variable with zero mean. With this model, a synthetic image with the speckle noise can be simulated. For example, fig. 1(a) is the original image and fig. 1(b) is the noisy image which can be simulated by the original image multiplied with a Rayleigh distribution fading variable.

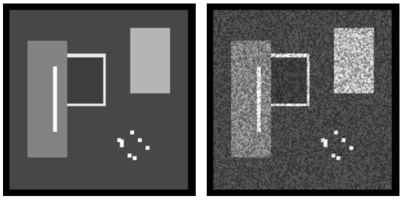

Fig. 1. Speckle Simulation (a) the original image, (b) the noisy image

3. DENOISING METHODS

A. Median Filter

Median filters are quite popular. Median filter replaces the value of pixel by the median of intensity values in the neighborhood of that pixel [6]. The median filter is defined as follows:-

$$\hat{f}(x,y) = median_{(s,t)\in S_{xy}}\{g(s,t)\} \quad (5)$$

Where, $g(s,t)$ is the corrupted image and S_{xy} is the set of coordinates in a rectangular subimage window centered at point (x,y).

B. Wiener Filter

Wiener filter is based on the least-squared principle, i.e. the filter minimizes the mean-squared error (MSE) between the actual output and the desired output. Wiener filter works on both the global statistics and local statistics. Let $g(x,y)$ is the brightness of the pixel (x,y) in a two dimensional $M \times N$ image. The local mean and variance are calculated over a $(2m+1)\times(2n+1)$ window.

The local mean and variance are defined below [2]:-

$$\bar{g}(x,y) = \frac{1}{(2m+1)(2n+1)} \sum_{s=x-m}^{x+m} \sum_{t=y-n}^{y+n} g(s,t) \quad (6)$$

$$Q(x,y) = \frac{1}{(2m+1)(2n+1)} \sum_{s=x-m}^{x+m} \sum_{t=y-n}^{y+n} \{(g(s,t) - \bar{g}(x,y))^2\} - \sigma_n^2 \quad (7)$$

The estimated denoised image is computed by

$$\hat{f}(x,y) = \bar{g}(x,y) + k(x,y)(g(x,y) - \bar{g}(x,y)) \quad (8)$$

Where $k(x,y)$ is given by

$$k(x,y) = \frac{Q(x,y)}{Q(x,y) + \sigma_n^2} \quad (9)$$

Where σ_n^2 is the noise variance. $Q(x,y)$ and σ_n^2 are both positive, $k(x,y)$ will lie between 0 and 1.

C. Bilateral Filter

Traditional filtering is domain filtering, and enforces closeness by weighing pixel values with coefficients that fall off with distance. Similarly, range filtering averages image values with weights that decay with dissimilarity. Range filtering preserves edges. As range filtering and domain filtering is combined, so the name bilateral filtering [3]. The bilateral filter is defined as below:-

$$\bar{f}(k,l) = \frac{\sum_{(x,y)\in N(s,t)} w(s,t,x,y)g(x,y)}{\sum_{(x,y)\in N(s,t)} w(s,t,x,y)} \tag{10}$$

Weight is computed as below:-

$$w(s,t,x,y) = exp\left\{-\frac{\big(g(s,t)-g(x,y)\big)^2}{2\sigma_r^2}\right\}.f\left(\sqrt{(s-x)^2+(t-y)^2}\right) \tag{11}$$

Where, function f takes the geometric distance into account and monotonically non-increasing. It may take many forms such as a Gaussian function, a box function, a constant and more. Here, σ_r is the intensity domain standard deviation. If Gaussian function is used than the weight is find out as:-

$$w(s,t,x,y) = exp\left\{-\frac{\big(g(s,t)-g(x,y)\big)^2}{2\sigma_r^2}\right\}.\exp\left(-\frac{(s-x)^2+(t-y)^2}{2\sigma_d^2}\right) \tag{12}$$

Where, σ_d is the spatial domain standard deviation.

D. Non-local means Filter

In this algorithm, discrete noisy image g is given then the estimated value of $NL[g](x)$, for pixel x, is computed as [4], [7]

$$NL[g](x) = \sum_{y\in I} w(x,y)g(y) \tag{13}$$

Where, the family of weights $w(x,y)$ depends on the similarity between the pixels x and y, and satisfy the usual conditions $0 \le w(x,y) \le 1$ and $\sum_y w(x,y) = 1$.

The similarity between two pixels x and y depends on the similarity of the intensity gray level vectors $g(N_x)$ and $g(N_y)$, where N_k denotes a square neighborhood of fixed size and centered at a pixel k. This similarity is measured as a decreasing function of the Euclidean distance.

$$d(x,y) = G_\rho \left\| g(N_x) - g(N_y) \right\|^2 \quad (14)$$

Where, G_ρ is a normalized Gaussian weighted function with zero mean and ρ standard deviation. Then $w(x,y)$ is calculated as,

$$w(x,y) = \left(\frac{1}{Z(x)}\right).\exp\left(\frac{-d(x,y)}{h^2}\right) \quad (15)$$

Where, $Z(x)$ is calculated as

$$Z(x) = \sum_{y \in I} exp\left(\frac{-d(x,y)}{h^2}\right) \quad (16)$$

Here $Z(i)$ is the normalized constant. The parameter h acts as a degree of filtering, controlling the decay of the exponential function. When $x = y$, the self similarity is high enough to yield over-weighting effect. In this case, we define,

$$w(x,y) = \max(w(x,y)), \forall x \neq y \quad (17)$$

4. IMAGE METRICS

A. PSNR

The PSNR is the peak signal-to-noise ratio, in decibels, between two images. This ratio is often used as a quality measurement between the original and a denoised image. Higher is the PSNR, better the quality of the denoised image. The MSE (Mean Square Error) is computed as follows:-

$$MSE = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \frac{\left(g(x,y) - \hat{f}(x,y)\right)^2}{M \times N} \quad (18)$$

PSNR is computed as follows:-

$$PSNR = 10 \log_{10}\left[\frac{255 \times 255}{MSE}\right] \quad (19)$$

B. RMSE

The RMSE is the root mean squared error. This is most frequently used quality measure between the original image and denoised image. Lesser is the RMSE, better is the quality of the image. The RMSE is calculated as below:-

$$RMSE = \sqrt{\frac{\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}(g(x,y) - \hat{f}(x,y))^2}{M \times N}} \quad (20)$$

5. RESULTS AND DISCUSSION

All experiments performed have been implemented in Visual Studio 0.6 on a PC with 2.30GHz Intel Core i3 CPU, 4GB RAM and 500GB HDD under Windows 7.0 environment. The experiment is performed on an ultrasound image of dimensions 512×512 which represent the appendix of human body as shown in fig. 2(a). Figure 3(a) represents the liver of human body. **Table 1** and **Table 2** are showing the PSNR and RMSE respectively at various noise levels(σ_h).

Table 1 PSNR values at different speckle noise levels

Filters	$\sigma_h = 0.01$	$\sigma_h = 0.02$	$\sigma_h = 0.03$	$\sigma_h = 0.04$	$\sigma_h = 0.05$	$\sigma_h = 0.06$
Median Filter	19.9620	18.4853	17.3661	16.4561	15.7285	15.0492
Weiner Filter	30.3483	27.2672	25.5979	24.4338	23.5582	22.7707
Bilateral Filter	31.0032	28.6185	26.5375	24.8269	23.4893	22.2974
NLM Filter	31.4904	29.7098	27.8594	27.7292	26.6238	25.5756

Table 2 RMSE values at different speckle noise levels

Filters	$\sigma_h = 0.01$	$\sigma_h = 0.02$	$\sigma_h = 0.03$	$\sigma_h = 0.04$	$\sigma_h = 0.05$	$\sigma_h = 0.06$
Median Filter	17.0638	30.3580	34.5331	38.3474	41.6982	45.0897
Weiner Filter	7.7469	11.0453	13.3858	15.3056	16.9290	18.5355
Bilateral Filter	7.1842	9.4540	12.0134	14.6284	17.0638	19.5737
NLM Filter	7.3325	8.2287	9.2476	10.4733	11.8946	13.4203

In case of median filter, the decrease in PSNR is from 19.9620 for $\sigma_h = 0.01$ to 15.0492 for $\sigma_h = 0.06$, that is the decrease of 4.9128. In case of Wiener filter, the decrease is 7.5776. For bilateral filter, the decrease is 8.7058. For non-local means filter, the decrease is 5.9148. For median filter, the increase in RMSE is 28.0259. For Wiener filter, the increase is 11.3513. For Bilateral filter, the increase is 12.3895. For non-local means filter, the increase is 6.0878. So according to PSNR and RMSE, non-local means filter performs better. For median filter and Wiener filter, size of window is 5×5. For Bilateral filter, the window size is 5×5. The spatial domain standard deviation (σ_d) used is $\sigma_d = 55$. The intensity domain standard deviation (σ_r) used is $\sigma_r = 40$. When the value of intensity domain standard deviation (σ_r) is large, then the spatial domain standard deviation (σ_d) has a little effect for small values. Also, a large σ_d blurs more, that is, it combines values from more distant image locations. In non-local means filter, the search window (t) is 15×15, the similarity window (f) is 5×5 and degree of filtering (h) is 20. In fig. 2 and fig. 3, (a) is the original image, (b) is the noisy image, (c) is the output of Median filter, (d) is the output of Weiner filter, (e) is the output of Bilateral filter, (f) is the output of Non-local means filter. As shown in the images, the non-local mean filter performs better than all the other filters. But this method is computationally slow.

Fig. 2. (a) Original image (b) Noisy image (c) Median filter (d) Weiner filter (e) Bilateral filter (f) Non-local mean filter

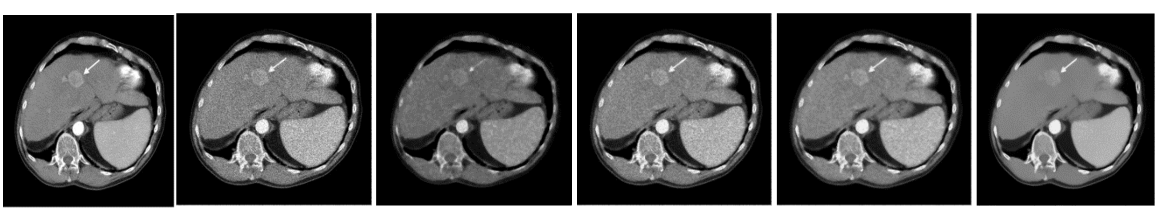

Fig. 3. (a) Original image (b) Noisy image (c) Median filter (d) Weiner filter (e) Bilateral filter (f) Non-local mean filter

6. CONCLUSION

As expected, median filter performs very poorly. The denoised image still contains noise. Median filter blurs the image and also in median filter, some of the pixels remain Unchanged. Median filter distorts the edges. Wiener filter performs better than median filter. But still, it does not remove the noise from the image properly and also it blurs the image. Bilateral performs better than previous two filters. It preserves edges. But at higher noise level, it still contains some amount of noise and the denoised image is over smoothened. NLM performs better than all the filters because it works on similar regions. But this method is computationally slow.

REFERENCES

[1] C. B. Burkhardt, Speckling in ultrasound b-mode scans, IEEE Trans. on Sonics and Ultrasonics, Vol. 25, 1978, 1-6.

[2] J. S. Lee, Digital image enhancement and noise filtering by Use of Local Statistics, IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol. 2, 1980, 165-168.

[3] C. Tomasi, R. Manduchi, Bilateral filtering for gray and color images, In Proceedings of IEEE Sixth International Conference on Computer Vision, Bombay, India, 1998, 839 - 846.

[4] A. Buades, B. Coll, J. M. Morel, A non-local algorithm for image denoising, In Proceedings of IEEE on Computer Vision and Pattern Recognition, Vol. 2, 2005, 60-65.

[5] T. C. Aysal, K. E. Barnar, Rayleigh-maximum-likelihood filtering for speckle reduction in ultrasound images, IEEE Trans. on Medical Imaging Vol. 26, 2007, 712-727.

[6] R. C. Gonzalez, R. E. Woods, Digital image processing, Pearson Education, India, 2008.

[7] Y. Guo, Y. Wang, T. Hou, Speckle filtering of ultrasonic images using a modified non local-based algorithm, Biomedical signal processing and control, 2011, 129-138.

[8] Information on http://splab.cz/en/download.databaze/ultrasound and http://www.ultrasound-images.com/heart-cvs.htm#Chordae%20tendinae%20calcification