35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Evaluation of Various Speckle Reduction Filters on Medical Ultrasound Images*

Shibin Wu, Qingsong Zhu and Yaoqin Xie Ph.D

Abstract— **At present, ultrasound is one of the essential tools for noninvasive medical diagnosis. However, speckle noise is inherent in medical ultrasound images and it is the cause for decreased resolution and contrast-to-noise ratio. Low image quality is an obstacle for effective feature extraction, recognition, analysis, and edge detection; it also affects image interpretation by doctor and the accuracy of computer-assisted diagnostic techniques. Thus, speckle reduction is significant and critical step in pre-processing of ultrasound images. Many speckle reduction techniques have been studied by researchers, but to date there is no comprehensive method that takes all the constraints into consideration. In this paper we discuss seven filters, namely Lee, Frost, Median, Speckle Reduction Anisotropic Diffusion (SRAD), Perona-Malik's Anisotropic Diffusion (PMAD) filter, Speckle Reduction Bilateral Filter (SRBF) and Speckle Reduction filter based on soft thresholding in the Wavelet transform. A comparative study of these filters has been made in terms of preserving the features and edges as well as effectiveness of de-noising. We computed five established evaluation metrics in order to determine which despeckling algorithm is most effective and optimal for real-time implementation. In addition, the experimental results have been demonstrated by filtered images and statistical data table.**

I. INTRODUCTION

Medical ultrasound (US) uses high frequency sound waves to create an image of living tissue. The basic technique is similar to the ones used in weather radars and submarine ultrasound systems. A sound signal is transmitted, and the reflected echo waves are used to create the image. Ultrasound, unlike most other imaging methods, can create truly real-time "movies" of the heart beating, the other organs deformable moving, contractions of bowel loops (peristalsis), and can even show blood flowing. It is safe, economical and non-harmful method for the patient. For its advantages, ultrasound imaging is one of the essential techniques for non-invasive medical diagnosis today. However, speckle noise is inherent in medical ultrasound images due to the ultrasound imaging principle. This noise trends to reduce the resolution and the contrast-to-noise ratio. Unfortunately, the features and tissue edges in ultrasound images are usually blurred, and the contrast and signal-to-noise ratio (SNR) are low. This is an obstacle for effective feature extraction, recognition, analysis, and edge detection, affects image interpretation by doctor and the accuracy of computer-assisted diagnostic techniques. In addition, the accurate and reliable features are substantially significant to image registration between ultrasound and MRI images.

Many speckle reducing algorithms based on noise modeling have been developed, and most of the noise is caused by the acquisition instrument, data transmission media, image quantization and discrete sources of radiation [1]. Speckle noise is a non-white and non-additive noise while it is known to be a correlated multiplicative noise so that many conventional noise removal techniques don't work well with it.Therefore the reduction of speckle without blurring the sharp features edges and contours is difficult [2].

There are two categories of speckle reduction techniques [3], namely compounding methods and post-processing techniques. The compounding speckle reduction methods include spatial and frequency compounding. These schemes rely on making separate images that have uncorrelated or partially correlated speckle patterns. Post-processing speckle reduction techniques decrease speckle after the ultrasound image is formed. When designing post-processing speckle reduction techniques, we have to make a tradeoff between increasing the contrast and reducing the speckle noise.

II. SPECKLE MODEL

The properties of speckle have been well investigated by many researchers [4][11]. Speckle is usually considered as a correlated multiplicative noise and can be transformed to additive noise by applying a logarithm operation. Kie B. has used mathematical model to analyze the coherent speckle in medical ultrasound images and corresponding to the model is given below:

$$g(i,j) = f(i,j) + h(i,j) * w(i,j) \tag{1}$$

where $g(i,j)$ is the real noise image, $f(i,j)$ is the unobservable original image, $h(i,j)$ and $w(i,j)$ are the point spreading function and the white Gaussian noise, respectively.

III. SPECKLE FILTERING

Several approaches have been proposed to reduce the speckle effect on ultrasound images. Speckle filtering consists of a window moving over each pixel in the image and applies a mathematical calculation and substitutes for the value of the central pixel under the window. The window

*This work is supported by grants from National Natural Science Foundation of China (NSFC: 81171402), Hong Kong and Macao Young Scholars (30928030), National Basic Research Program 973 (2010CB732606) from Ministry of Science and Technology of China.

Shibin Wu is with the Key Laboratory for Health Informatics, Shenzhen Institute of Advanced Technology Chinese Academy of Sciences, Shenzhen, Guangdong 518055 PRC (corresponding author, phone:86-1-3410-145-521;e-mail: sb.wu@siat.ac.cn)

Qingsong Zhu is with the Key Laboratory for Health Informatics, Shenzhen Institute of Advanced Technology Chinese Academy of Sciences, Shenzhen, Guangdong 518055 PRC (e-mail: qs.zhu@siat.ac.cn)

Yaoqin Xie is with the Key Laboratory for Health Informatics, Shenzhen Institute of Advanced Technology Chinese Academy of Sciences, Shenzhen, Guangdong 518055 PRC (e-mail: yq.xie@siat.ac.cn)

moves along the image one pixel at a time until it covers the entire image. This section provides a brief definition and mathematical formula of various speckle reduction filters.

A. Lee Filter

The Lee filters [5] are based on the minimum mean square error (MMSE), producing speckle free image governed by the following relationship:

$$U(x, y) = I(x, y)W(x, y) + I'(x, y)\left(1 - W(x, y)\right) \quad (2)$$

where I' is the mean value of the intensity within the filter kernel, and $W(x, y)$ is the adaptive filter coefficient calculated by the following formula:

$$W(x, y) = 1 - \frac{C_B^2}{C_I^2 + C_B^2} \quad (3)$$

where C_I is the coefficient of variation of the noised image and C_B is the coefficient of variation of the noise.

B. Frost Filter

The Frost filter [6] is an adaptive and exponentially weighted averaging filter based on the coefficient of variation which is the ratio of the local standard deviation to the local mean of the degraded image. This filter is described by mathematical expression below:

$$DN = \sum_{n \times n} k\alpha e^{-\alpha|t|} \quad (4)$$

where k is a normalization constant, α is $(4/n\sigma'^2) \cdot (\sigma^2/\bar{I}^2)$, $\bar{I}$ is the local mean, σ is the local variance, σ' is image coefficient of variation, $|t| = |X - X_0| + |Y - Y_0|$ and n is the moving window size.

C. Median Filter

The median filter [6] is a spatial non-linear filter, reducing pulse or spike noise by replacing the middle pixel value in the window with the median value of its neighbors in the window. The major problem of the median filter is its high computational cost, and its time complexity is $O(N \cdot \log N)$ for sorting N pixels.

D. Speckle Reduction Anisotropic Diffusion Filter (SRAD)

SRAD technique is based on a partial differential equation (PDE) and the MMSE, which can be related directly to the Lee and Frost window-based filters [7][8]. Thus, according to the PED, the equation of the SRAD [8] can be briefly described as follows:

$$\begin{cases} \partial I(x, y; t)/\partial t = div\left[c(q)\nabla I(x, y; t)\right] \\ I(x, y; 0) = I_0(x, y; 0), \left(\partial I(x, y; t)/\vec{n}\right)|\partial\Omega = 0 \end{cases} \quad (5)$$

where $I_0(x, y)$ represents the intensity image, $I(x, y; t)$ is the output image, 'div' the divergence operator, $\partial\Omega$ denotes the border Ω, $\vec{n}$ is the outer normal $\partial\Omega$, and $C(q)$ is the diffusion coefficient and can be calculated as follows:

$$C(q) = \frac{1}{1 + [q^2(x, y; t) - q_0^2(t)]/[1 + q_0^2(t)]} \quad (6)$$

where $q(x, y; t)$ is the instantaneous coefficient of variation determined by:

$$q(x, y; t) = \sqrt{\frac{(1/2)(|\nabla I|/I)^2 - (1/4^2)(\nabla^2 I/I)^2}{[1 + (1/4)(\nabla^2 I/I)]^2}} \quad (7)$$

where ∇ is the gradient operator, $||$ denotes the magnitude. The coefficient $q_0(t)$ is estimated below

$$q_0(t) = \frac{\sqrt{var[z(t)]}}{\overline{z(t)}} \quad (8)$$

where $var[z(t)]$ and $\overline{z(t)}$ are the intensity variance and mean over a homogeneous area at t, respectively.

E. Anisotropic Diffusion Filter

Perona and Malik [9] proposed a nonlinear anisotropic diffusion filter to avoid the blurring original image and localization problems of linear diffusion linear filtering, It is called Perona-Malik Anisotropic Diffusion (PMAD) filter. The PMAD is based on the following equation:

$$\partial_t u = div(g|\nabla u|^2 \nabla u) \quad (9)$$

where ∇ is the gradient operator, ∇u is the image gradient, $||$ denotes the magnitude, and 'div' the divergence operator. The equation 9 uses diffusivities such as:

$$g(|\nabla u|^2) = \frac{1}{1 + |\nabla u|^2/\lambda^2}(\lambda > 0) \quad (10)$$

where λ is an edge magnitude parameter.

F. Speckle Reduction Bilateral Filter (SRBF)

SRBF is described in [10]. A brief description of the classical SRBF is described in this section, following the characterization of the speckle noise. Then the framework of the SRBF is adapted to the a priori knowledge on the speckle noise statistics and estimated speckle size. The general SRBF function can be expressed as:

$$h(p) = \Gamma^{-1}(p) \int_{\Omega(p)} f(\xi)c(\xi, p)s(f(\xi), f(p))\mathrm{d}\xi \quad (11)$$

with the normalization factor:

$$\Gamma(p) = \int_{\Omega(p)} c(\xi, p)s(f(\xi), f(p))\mathrm{d}\xi \quad (12)$$

where f is the original image, h is the filtered image, $\Omega(p)$ is the spatial neighborhood of the coordinate of a generic pixel p in the image and ξ is the integration variable representing pixels coordinate. In addition, $c(\xi, p)$ and $s(f(\xi), f(p))$ are represented by formulas of (13) and (14), respectively.

$$c(\xi, p) = \exp\left(-\frac{\|p - \xi\|^2}{2\sigma_c^2}\right) \quad (13)$$

$$s(f(\xi), f(p)) = \exp\left(-\frac{(f(p) - f(\xi))^2}{2\sigma_s^2}\right) \quad (14)$$

where σ_c is the standard deviation of the Gaussian on the spatial support and σ_s is the standard deviation in the rand domain Ω.

G. Speckle Reduction based on Soft Thresholding in the Wavelet Transform (SRTW)

Wavelets are basically mathematical functions which break up the data in different frequency components. All the wavelet filters use wavelet thresholding for de-noising [15]. Speckle noise is a high-frequency component of the image and appears in wavelet coefficients. M.S. Devi and V. Radhika present speckle reduction based on soft thresholding in the wavelet transform for ultrasonic images. Thresholding rule determines how to modify the wavelet coefficients and reflects the corresponding processing strategy according to different wavelet coefficients. The basic procedure for all thresholding methods involves three steps: (i) Compute the DWT (Discrete Wavelet Transform) or QWT (Quaternion Wavelet Transform) of the input image; (ii) Threshold the wavelet coefficients; (iii) Perform the inverse DWT or QWT of the thresholding result to obtain the de-noised image [15-17]. Furthermore, there are two different frequently used thresholding functions , which uses a hard threshold and a soft threshold.

IV. Evaluation Metric of Filtering

In this section, we present some common measurements that are needed to evaluate the performance of speckle reduction filters for ultrasound images. To quantify the performance of a speckle noise reduction filtering algorithms in terms of efficiency and enhancing the significant image information, we calculate MSE, SNR, PSNR, AD and SI for the filtered images [5][11-14].

A. Mean Square Error (MSE)

MES is widely used to find the total amount of differences between the original and the de-noised image. Higher and lower MSE values indicate larger and smaller differences between the original and filtered image, respectively. MSE is equal to zero for identical images. It is 255 for completely dissimilar images. It is calculated as follows:

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(X_{i,j} - X'_{i,j}\right)^2 \tag{15}$$

B. Signal-to-Noise Ratio (SNR)

SNR is a common measurement to evaluate the speckle reduction in the case of multiplicative noise by computing the ratio between the original and the de-noised image. Higher SNR values show that the filtering effect is better, and filtered image quality is much higher.

C. Peak Signal-to-Noise Ratio (PSNR)

PSNR is measurement of the performance of the speckle noise reduction. It is a ratio between the maximum possible power of the signal and the noise image. The PSNR can be calculated as follows:

$$PSNR = 10\log_{10}\frac{(2^n-1)^2}{MSE} = 10\log_{10}\left(\frac{255^2}{MSE}\right) \tag{16}$$

Higher PSNR values correspond to a better image quality. For identical images, the MSE becomes zero and the PSNR is undefined.

D. Average Difference (AD)

AD is the mean difference between original and filtered image divided by the size of the image. Its maximal value corresponds to dissimilar image and its minimal value corresponds to similar images. It is calculated as follows:

$$AD = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}|X_{i,j} - X'_{i,j}| \tag{17}$$

E. Speckle Index (SI)

SI is a measure of speckle reduction in terms of average contrast of the image. Lower value of SI corresponds to improved image quality. The SI is defined as follows:

$$SI = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{\sigma(i,j)}{\mu(i,j)} \tag{18}$$

where $\sigma(i,j)$ and $\mu(i,j)$ are the standard deviation and means corresponding to a neighbor domain, respectively.

V. Experimental Results and Discussion

In this section we discuss the experimental results obtained by applying the previously described speckle reduction filters on ultrasound kidney and liver images with size of 366×688 pixels. The evaluation measurements were done for each despeckled image, that was used to compare the effectiveness of filters. Moreover, it is important to evaluate the performance of various speckle reduction filters. Figure 1 shows a representative filtered results of ultrasound image, involving a complete kidney. Furthermore, the corresponding to various performance metrics are calculated for filtered images and shown in data Table I.

From Figure 1, we can see that the SRBF produces an obvious example of speckle reduction and diffusion processing, and the features of tissues are enhanced. The SRBF presents a superior edge preserving behavior, and its filtering results are of the best visual appearance in our experiments. Secondly, the speckle filter based on the wavelet transform demonstrated better results in our experiments. What's more, the filtered results of the SRAD and PMAD filters also can be used to prove that the two filters can improve the image quality. The Lee, Frost and Median filters slightly improve the information of the edges and reduce some speckle noise, but in our experiments they didn't demonstrate obvious improvement of image quality. The Frost filter even blurred the feature of tissue to some extent. Finally, Lee, Frost and Median filters belong to the spatial adaptive group of filters, which uses a moving filter window and calculates the statistical information of all pixels gray values such as the local mean and the local variance. The central pixel's output value is dependent on the computed statistical information. The SRBF, SRAD and PMAD filters are the anisotropic diffusion filter, and applied directly on the ultrasound image for removing speckle noise by solving partial differential equation. The SRTW belongs to the spatial and frequency domain group of filters and divides the input signal into subbands which are de-speckled by thresholding. Then all subbands can be reconstructed to produce filtered image by the inverse wavelet transform. Therefore, the visualization of the filtered images from SRBF, SRAD, PMAD and SRTW are better than the ones of Lee, Frost and Median filters.

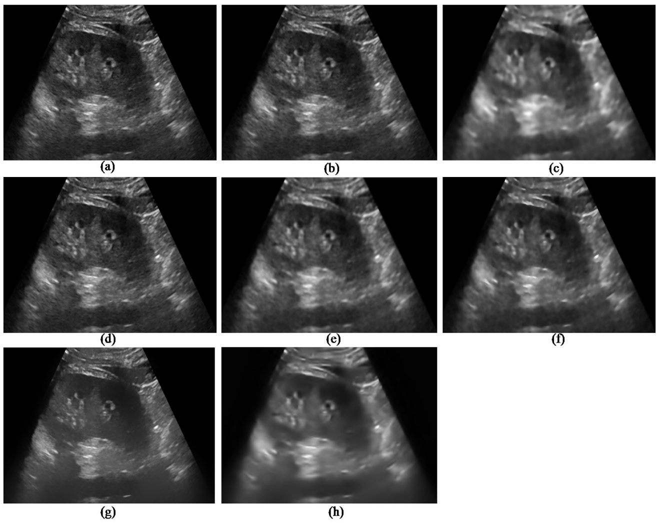

Fig. 1. Original and filtered images. (a) Original image; (b) Lee; (c) Frost; (d) Median; (e) SRAD; (f) PMAD; (g) SRBF; (h) SRTW.

From the results in Table I, the SNR and PSNR of the SRBF filter are larger than those of the other filters in all experiments, and their metrics of MES, AD and SI are smaller than other filters. Thus, the SRBF seems to be more suitable for speckle reduction in ultrasound images compared to other algorithms. Although the interval scale between all metrics of the filters is not large, it is worthwhile to note that the mathematical expressions of MSE, SNR, PSNR, AD and SI are rather significant. These metrics are proposed for calculating the difference of each pixel pair between original and filtered images.

TABLE I

COMPUTED PERFORMANCE METRICS OF THE VARIOUS SPECKLE REDUCTION FILTERS (NOTE: THE SI VALUE OF ORIGINAL IMAGE EQUALS **3.6463E-6**)

Filter	MSE	SNR	PSNR	AD	SI
Lee	29.4499	16.0549	31.4400	0.0309	3.6008e-6
Frost	57.1073	13.1789	30.5639	0.0841	3.4730e-6
Median	101.7561	10.6702	28.0552	0.0971	3.6226e-6
SRAD	61.9800	12.8233	30.2083	0.0489	3.5415e-6
PMAD	37.4021	15.0168	32.4018	0.0293	3.5423e-6
SRBF	**26.8844**	**16.4508**	**33.8358**	**0.0229**	**3.4157e-6**
SRTW	52.7967	10.5751	30.9311	0.0361	3.5573e-6

VI. CONCLUSION

In this paper, we evaluated seven algorithms of speckle noise reduction on medical ultrasound images. We compared the results for filtering as well as the five performance metrics. These filtering algorithms from the previously described were implemented in MatLab 2011a and tested in more than 50 ultrasound images for two different human body organs including liver and kidney. During all experiments the algorithms demonstrated reliable performance. and produced performance metrics depending on filter algorithms' parameters adjustment and limited image content. The filtered results using the spatial adaptive filters show that have rather similar visual appearance. On the other hand, from the visualization of filtered images, the anisotropic diffusion filters exhibit high performance of speckle noise reduction and the ability to preserve and even enhance the edges of the images when compared with the spatial filters. Furthermore, the SRBF is a fast and flexible algorithm and offers a better quality of speckle noise reduction and features enhancement than those of the other filters.

REFERENCES

[1] Faten A. Dawood, Rahmita W. Rahmat, and Suhaini B. Kadiman, etc., "Effect comparison of speckle noise reduction filters on 2D-Echocardigraphic images," World Academy of Science, Engineering and Technology, Issue 69, pp. 475−480, 2012.

[2] M.Saranya, and C. Saraswathy, "Speckle reduction in Ultrasound image," International Journal of Electronics and Computer Science Engineering, ISSN: 2277−1956, Vol. 1, No. 2, pp. 342−347, 2012.

[3] Joshua S. Ullom, Michael L. Oelze, and Jose R. Sanchez, "Speckle reduction for Ultrasound imaging using frequency and compounding and despeckling filters along with coded excitation and pulse compression," Advances in Acoustics and Vibration, Vol. 2012, 2012.

[4] Kie B. Eom, "Speckle reduction in Ultrasound images using non-isotropic adaptive filtering," Ultrasound in Medicine & Biology, Vol. 37, No. 10, pp. 1677−1688, 2011.

[5] R. Sivakumar, M. K. Gayathri and D. Nedumaran, "Speckle filtering of Ultrasound B-scan images - A comparative study between spatial and diffusion filters," 2010 IEEE Conference on Open System (ICOS 2010), pp. 80−85, 2010.

[6] Raman Maini, Himanshu Aggarwal, "Performance evaluation of various speckle noise reduction filters on medical images," International Journal of Recent Trends in Engineering. Vol. 2, No. 4, pp. 22−25, 2009.

[7] Jadwiga Rogowska and Mark E. Brezinski, "Evaluation of the adaptive speckle suppression filter for coronary optical coherence tomography imaging," IEEE Transactions on Medical Imageing, Vol. 19, No. 12, pp. 1261−1266, 2000.

[8] Yongjian Yu and Scott T. Acton, "Speckle reducing anisotropic diffusion," IEEE Transactions on Image Processing, Vol. 11, No. 11, pp. 1260−1270,2002.

[9] Joachim Weickert, "Anisotropic diffusion in image processing,"B.G. Teubner (Stuttgart), pp. 14−29, 1998.

[10] Simone Balocco, Carlo Gatta, Oriol Pajol, Josepa Mauri, and Petia Radeva, "SRBF: Speckle reducing bilateral filtering," Ultrasound in Medical & Biology, Vol. 36, No. 8, pp. 1353−1363, 2010.

[11] Ahmet M. Eskicioglu and Paul S. Fisher, "Image quality measures and their performance," IEEE Transactions on Communications, Vol. 43, No. 12, pp. 2959−2965, 1995.

[12] YanHui Guo, H. D. Cheng, JiaWei Tian and YingTao Zhang, "A novel approach to speckle reduction in Ultrasound imaging," Ultrasound in Medical & Biology, Vol. 35, No. 4, pp. 628−640, 2009.

[13] Rajeev Srivastava, JRP Gupta, Harish Parthasrthy, "Comparison of PDE based and other techniques for speckle reduction from digitally reconstructed holographic images," Optics and Lasers in Engineering, Vo. 48, No. 5, pp. 626−653, 2010.

[14] Zhou Wang, and Alan C. Bovik, "A universal image quality index," IEEE Signal Processing Letters, Vol. 9, No. 3 pp. 81−84, 2002.

[15] J. Jin, etc., "Ultrasonic speckle reduction based on soft thresholding in quaternion wavelet domain," Proc. Instrumentation and Measurement Technology Conference (I2MTC), pp. 13−16, 2012.

[16] M.S. Devi, V. Radhika, "Comparative Approach for Speckle Reduction In Medical Ultrasound Images," IJART, Vol. 1, pp.7−11, 2011.

[17] M.C. Nicolae, L. Moraru, and L. Onose, "Comparative Approach for Speckle Reduction in Medical Ultrasound Images," ROMANIAN J. BIOPHYS., Vol. 20, pp. 13−21, 2010.