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Despeckling of Medical Ultrasound Images of Kidney-Performance Evaluvation of Spatial Filters

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Abstract: Ultrasound imaging is a widely used medical diagnostic technique capable of producing real time images of soft tissues like kidney, liver, gallbladder, spleen etc. Speckle noise is an ubiquitous phenomena found in all coherent imaging modalities that degrades both the image quality and the visual interpretation of the acquired data. Several adaptive spatial domain filters have been documented to deal with this issue. The objective of this study is to identify an efficient and optimum despeckling filter in terms of quantitative metrics. In this scope, Frost, Lee, Kuan, Enhanced Lee and Frost, Wiener, Diffusion, Squeeze Box Filters (SBF) have been tested in detail on real time ultrasound kidney images. To assess the performance of filters, quantitative metrics such as Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR), Average Difference (AD), Mean Square Error (MSE), Root Mean Square Error (RMSE), Structural Content (SC), Universal Quality Index (UQI), Normalised Cross Correlation (NCC) and Structural Similarity (SSIM) have been calculated. Experimental results show that SBF and Anisotropic diffusion filters with little number of iteration outperform over the others in terms of speckle reduction.

Keywords: Filtering techniques, speckle noise, speckle reduction, ultrasound imaging

INTRODUCTION

Speckle noise is a phenomenon that is inherent in all coherent imaging modalities in which images are produced by interfering echoes of a transmitted waveform that emanate from heterogeneous tissues. The presence of speckle noise has been documented by researchers since 1976. Goodman (1976) described the fundamental and statistical properties of speckle noise. More relevant description of speckle has been proposed by Wagner *et al*. (1983), (1986). These studies advocate the necessity of rejecting speckle through filtering technique to improve the perceptual quality of the images. In this study the mathematical model (Goodman, 1976) is considered for the analysis of speckle noise as:

$$J_{(x,y)} = \left(P_{(x,y)} * I_{(x,y)}\right)\eta_{\times(x,y)} \quad (1)$$

where, $I_{(x,\,y)}$ is the ideal image. $P_{(x,\,y)}$ is the point spread function. $\eta x_{\times\ (x,\ y)}$ is the sample wise independent and uncorrelated multiplicative noise. This multiplicative model could be made equivalent to the additive model as:

$$J_{(x,y)} = \left(P_{(x,y)} * I_{(x,y)}\right) + \eta_{+(x,y)} \quad (2)$$

Recent years, several techniques have been proposed by researchers to remove speckles in ultrasound images. All these techniques can be grouped in to two methods as Compounding method and Post acquisition method. Many studies have been proposed based on compounding techniques (Donnel and Silverstein, 1988; Trahey *et al*., 1986; Lie and Chen, 2002). Compounding method needs hardware modification and hence complexity is high. On the other hand post acquisition method does not require any hardware modifications. All the post acquisition methods are further categorized into single scale and multi-scale. Although both of these filters are capable of suppressing speckles, they still seem to remove fine details as they possess low pass characteristics.

For automatic or semi automatic segmentation the existence of speckle is undesirable and speckle filtering is the first and foremost step to be carried out. An appropriate method of speckle reduction is one which enhances the signal to noise ratio while preserving the edge details. Here an attempt is made in evaluating the performance of filters in terms of SNR, PSNR, MSE, RMSE, UQI, SC, NCC and SSIM.

METHODOLOGY

Speckle filtering techniques: Speckle filtering in the spatial domain is characterized by moving a kernel over each pixel in the image and applying a weighted average calculation using sub region statistics for estimating statistical measures over the defined kernel. Usual kernel window size chosen is odd and ranges from 3×3, to 15× 15. In all these techniques speckle noise model assumed has a multiplicative form.

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Frost filter: Frost filter (Raman and Himanshu, 2009) is a spatial domain adaptive filter that is based on multiplicative noise order. It adapts to noise variance within the filter window by applying exponentially weighting factor M. The response of the filter is given by:

$$R_{(x,y)} = \frac{\left(\sum P_n * M_n\right)}{\sum M_n} \tag{3}$$

where,

$$M_n = \exp\left(-D*\left(\frac{\sigma_n}{\mu_n}\right)^2 * T\right) \tag{4}$$

P_n is the image pixels in the filter window. D is the damping factor, which determines the extent of the potential damping for the image. Typical value of D is 1. σ_n is the standard deviation of the filter window. μ_n is the local mean T is the absolute value of the pixel distance between the centre pixel to its surrounding pixels in the filter window. For a 3×3 filter window the absolute pixel distance with respect to the centre pixel has been defined as:

2	1	2
1	0	1
2	1	2

This can be extended for a 5×5 filter window.

Lee and Kuan filter: Lee and Kuan (Jappreet *et al*., 2011; Kalaivani and Wahidabanu, 2009; Nadia, 2006) filters are based on the Minimum Mean Square Error (MMSE) which produces despeckled image according to the equation given by Jappreet *et al*. (2011) as:

$$R_{(x,y)} = I_{(x,y)} W_{(x,y)} + I'_{(x,y)}\left(1 - W_{(x,y)}\right) \tag{5}$$

where, $I'_{(x,y)}$ is the mean value of the intensity within the filter window and $W_{(x,y)}$ is the adaptive filter coefficient determined using:

$$W(x,y) = \begin{cases} 1 - \dfrac{C_b^2}{C_i^2 + C_b^2} & \text{for Lee} \\ \dfrac{1 - C_b^2 / C_i^2}{1 + C_b^2} & \text{for Kuan} \end{cases} \tag{6}$$

where, C_i is the coefficient of variation of the noised image and C_b is the coefficient of variation of the noise.

Enhanced Frost and lee filter: The enhanced Frost filter (Sivakumar *et al*., 2010) is the modification of Frost filter and is evaluated using the equation given by:

$$W_{(x,y)} = e^{-k\, func(CI)} \tag{7}$$

where, *func* C_I is a hyperbolic function.

Wiener filter: Wiener filtering (Jain, 1989; Gonzalez and Richard, 2008; Kailath, 1976) is based on the local image variance. Local image variance is high, then smoothing is little and vice versa. It is given by the following expression:

$$f(u,\upsilon) = \left[\frac{H(u,\upsilon)}{H(u,\upsilon)^2 + \left[S_n(u,\upsilon) / Sf(u,\upsilon)\right]}\right] \tag{8}$$

where, $H(u, \upsilon)$ is the degradation function and $H(u, \upsilon)^*$ is its complex conjugate. $G(u, \upsilon)$ is the degraded image. Functions $Sf(u, \upsilon)$ and $Sn(u, \upsilon)$ are the power spectra of the original and noisy image.

Anisotropic diffusion filter (PMAD): Anisotropic diffusion filter proposed by Sivakumar *et al*. (2010) is a generalization of the diffusion process. The diffusion equation is a PDE whose discrete form is given by:

$$I_S^{t+\Delta t} = I_S^t + \overline{\left(\Delta t / \left|\overline{\eta s}\right|\right)} + \sum_{\rho \in \overline{\eta} s} c\left(\nabla I_{S,P}^t\right) \nabla I_{S,P}^t \tag{9}$$

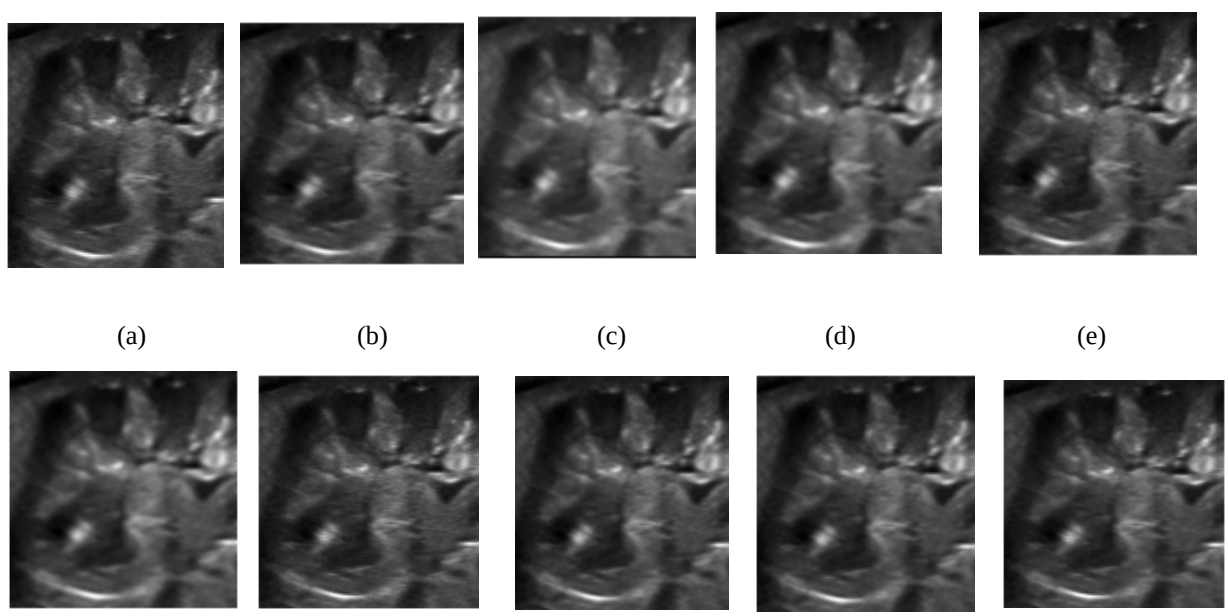
where, I^t_S is the sampled image, S, P is the pixel position in 2D grid and Δt is the time step size $\overline{\eta} s$ represents the spatial neighbourhood of pixel $\left|\overline{\eta} s\right|$ is the number of pixels in the window.

Squeeze box filter: Squeeze Box Filter (SBF) proposed by Tay *et al*. (2010) focuses on removing local extremas. These local extremas have been considered as outliers and are smoothed aggressively. White Gaussian noise of zero mean and a small variance is initially and periodically added to the image to be despeckled. In each iteration, the locations of the local extremas are found and replaced by a mean value which is estimated in that neighbourhood excluding these extremas.

Filter assessment: First, for medical images, quality of the filters in terms of their efficiency in removing speckles and preserving the useful information (Sivakumar *et al*., 2010) can be objectively measured by means of terms such as SNR, PSNR, MSE, RMSE, SC, UQI, NCC and SSIM Performance metrics, their mathematical expression and their usefulness are presented in Table 1.

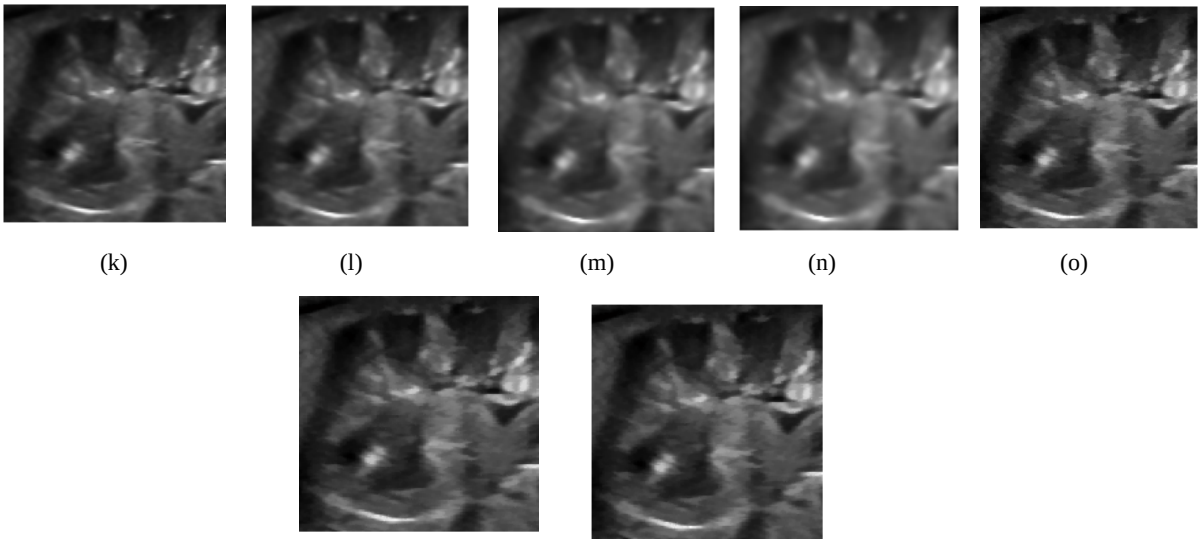
Table 1: Mathematical expressions of performance metrics

Performance metrics	Mathematical expression	Use
Mean Square Error	$MSE = \frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N}\left(X_{j,k} - X'_{j,k}\right)^2$	Measures the quality change between the original image and the despeckled image
Root mean Square Error	$RMSE\sqrt{\frac{1}{MN}\sum_{k=1}^{N}\left(X_{j,k} - X'_{j,k}\right)^2}$	Measures the square root of the squared error averaged over an pixel window. It is the best approximation of the standard error
Signal to Noise Ratio (SNR)	$SNR = 10\log_{10}\frac{\sum_{j=1}^{M}\sum_{k=1}^{N}\left(X_{j,k}^{2} - X'^{2}_{j,k}\right)}{\sum_{j=1}^{M}\sum_{k=1}^{N}\left(X_{j,k} - X'_{j,k}\right)^2}$	Compares the level of desired signal with respect to the level of background noise
Peak Signal to Noise Ratio	$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right)$	Provides the quality of the image in terms of power of the original signal and denoised signal
Structural Content	$SC = \frac{\sum_{j=1}^{M}\sum_{k=1}^{M} X^2_{j,k}}{\sum_{j=1}^{M}\sum_{k=1}^{M}\left(X_{j,k}\right)^2}$	Measures the similarity between the original and denoised image
Universal Quality Index	$UQI\ \frac{\sigma XX'}{\sigma_X \sigma_{X'}} \cdot \frac{2\overline{X}\,\overline{X}'}{\left(\overline{X}\right)^2 + \left(\overline{X}'\right)^2}\frac{2\sigma_X \sigma_{X'}}{\left(\sigma_X\right)^2 + \left(\sigma_{X'}\right)^2}$	Measures loss of correlation, luminance distortion and contrast distortion between original image and despeckled image
Normalised Cross Correlation	$NCC = \frac{\sum_{j=1}^{M}\sum_{k=1}^{N}\left(x_{J,k}\right)\left(x'_{j,k}\right)}{\sum_{j=1}^{M}\sum_{k=1}^{N} x_{j,k}^2}$	Measures the similarity between the original and despeckled image
Structural Similarity	$SSIM = \frac{\left(2\overline{X}\,\overline{X}' + c_1\right)\left(2\sigma_{XX'} + c_2\right)}{\left(\overline{X}^2 + X'^2 + c_1\right)\left(\sigma_X^2 + \sigma_{X'}^2 + c_2\right)}$	Measures the structural similarity between the original image and the depeckled image. Its value lies between -1 and +1. C_1 and C_2 are 0.01 and 0.03 dr, respectively, (Where dr is the dynamic range of the intensity)



(a) (b) (c) (d) (e)

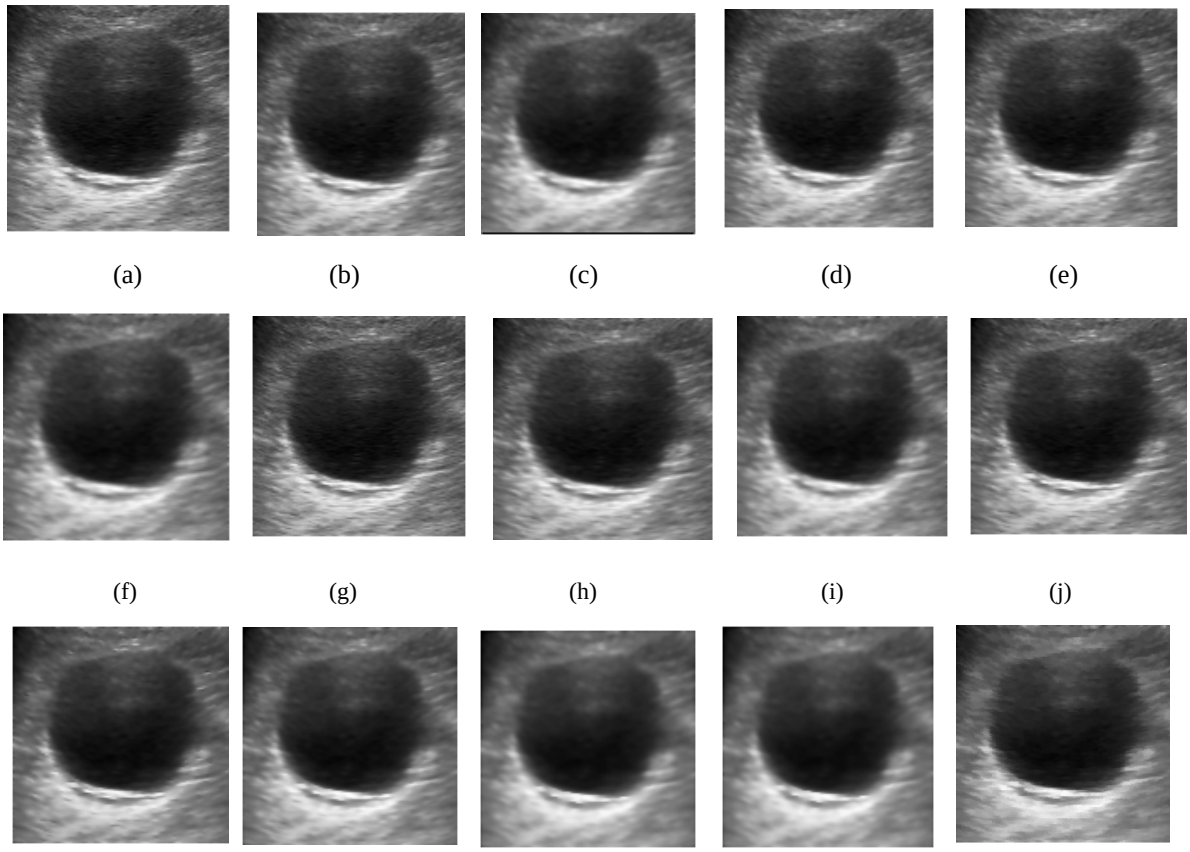
(f) (g) (h) (I) (j)



(k) (l) (m) (n) (o)

(p) (q)

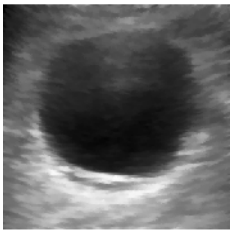
Fig. 1: Original and despeckled images of kidney, (a) Original image, (b) Frost with 3×3 window (c) Frost with 5×5 window (d) Enhanced frost with 3×3 window, (e) Lee with 3×3 window, (f) Lee with 5×5 window, (g) Enhanced lee with 3×3 window, (h) Kuan with 3×3 window, (i) Kuan with 5×5 window, (j) Wiener with 3×3 window, (k) Wiener with 5×5 window, (l) PMAD on 5 iterations (m) PMAD on 10 iterations, (n) PMAD on15 iterations, (o) SBF on 5 iterations, (p) SBF 10 iterations, (q) SBF5 on 15 iterations



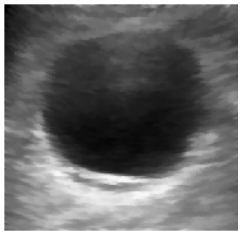
(a) (b) (c) (d) (e)

(f) (g) (h) (i) (j)

(k) (l) (m) (n) (o)



(p)



(q)

Fig. 2: Original and despeckled images of kidney, (a) Original image, (b) Frost with 3X3 window, (c) Frost with 5X5 window, (d) Enhanced frost with 3×3 window, (e) Lee with 3×3 window, (f) Lee with 5×5 window, (g) Enhanced lee with 3×3 window, (h) Kuan with 3×3 window, (i) Kuan with 5×5 window, (j) Wiener with 3×3 window, (k) Wiener with 5×5 window, (l) PMAD on 5 iterations, (m) PMAD on 10 iterations, (n) PMAD on 15 iterations, (o) SBF on 5 iterations, (p) SBF 10 iterations, (q) SBF5 on 15 iterations

Table 2: Performance metrics of the implemented despeckling filters corresponding to the images shown in Fig. 1

Filter name	MSE	RMSE	PSNR	SNR	SC	NCC	UQI	SSIM
FROST 3X3	4.0676	2.0168	41.6188	8.7510	1.0065	1.0028	0.0145	0.0180
FROST 5X	550.5590	7.1105	30.6741	3.1591	1.0225	1.0058	0.0261	0.0297
LEE 3X3	4.1085	2.0270	41.5752	8.6932	1.0064	1.0028	0.0145	0.0181
LEE 5X5	17.3996	4.1713	35.3067	6.0577	1.015	1.0056	0.0344	0.0380
KUAN 3X3	4.1085	2.0270	41.5752	8.6932	1.0064	1.0028	0.0145	0.0181
KUAN 5X5	17.3996	4.1713	35.3067	6.0577	1.015	1.0056	0.0344	0.0380
E FROST 3X3	5.4553	2.3356	40.3440	8.0394	1.0074	1.0031	0.0166	0.0202
E_LEE 3X3	0.0141	0.1188	66.2146	11.3585	1.0000	1.0000	0.0002	0.0036
WIENER 3X3	2.5596	1.5999	43.6304	8.2326	1.0036	1.0015	0.0079	0.0115
WIENER 5X5	8.7889	2.9646	38.2728	6.3203	1.008	1.0031	0.0159	0.0195
PMAD 5 itrns1	6.7223	4.0893	35.4792	7.4962	1.0202	1.0083	0.0290	0.0326
PMAD 10 Iitrns	37.0780	6.0892	32.0210	6.3570	1.0349	1.0134	0.0471	0.0507
PMAD 15 itrns	57.7411	7.5988	30.0973	5.7162	1.0475	1.0174	0.0614	0.0650
SBF 5 itrns	92.0853	9.5961	28.0702	10.9642	0.8052	0.8948	0.1798	0.1821
SBF 10 itrns	89.1822	9.4436	28.2093	10.7319	0.8182	0.9014	0.1793	0.1816
SBF 15 itrns	88.3243	9.3981	28.2513	10.7068	0.8205	0.9026	0.1777	0.1800

Table 3: Performance rmse metrics of the implemented despeckling filters corresponding to the image shown in Fig. 2

Filter name	MSE	RMSE	PSNR	SNR	SC	NCC	UQI	SSIM
FROST 3X3	22.8690	4.7822	34.4699	5.2331	1.0072	1.0025	0.0115	0.0126
FROST 5X5	231.2010	15.2053	24.4225	1.0941	1.0285	1.0032	0.0287	0.0299
LEE 3X3	23.1102	4.8073	34.4244	5.1746	1.0071	1.0025	0.0115	0.0127
LEE 5X5	69.4850	8.3358	29.6435	2.8256	1.0126	1.0030	0.0217	0.0228
KUAN 3X3	23.1102	4.8073	34.4244	5.1746	1.0071	1.0025	0.0115	0.0127
KUAN 5X5	69.4850	8.3358	29.6435	2.8256	1.0126	1.0030	0.0217	0.0228
E FROST 3X3	30.5446	5.5267	33.2131	4.4152	1.0079	1.0025	0.0129	0.0140
E_LEE 3X3	0.0578	0.2405	60.4395	4.3809	1.0000	1.0000	0.0001	0.0013
WIENER 3X3	15.8888	3.9861	36.0515	5.7683	1.0056	1.0021	0.0086	0.0097
WIENER 5X5	43.2502	6.5765	31.7025	3.7645	1.0097	1.0028	0.0148	0.0160
PMAD 5 itrns	53.5577	7.3183	30.7742	4.8449	1.0155	1.0052	0.0202	0.0213
PMAD 10 iitrns	91.3539	9.5579	28.4551	4.3891	1.0240	1.0076	0.0291	0.0302
PMAD 15 itrns	118.4436	10.8832	27.3273	4.3537	1.0310	1.0098	0.0353	0.0364
SBF 5 itrns	116.3000	10.7800	27.4100	11.4000	0.8700	0.9300	0.0400	0.0500
SBF 10 itrns	141.4200	11.8900	26.5600	11.1000	0.8500	0.9200	0.0500	0.0500
SBF 15 itrns	149.7100	12.2400	26.3100	11.0300	0.8500	0.9200	0.0500	0.0500

EXPERIMENTAL RESULTS AND ANALYSIS

Ultrasound images used in this experimental study were obtained from the KGS scan centre, Aruppukottai. The dataset consists of 50 unmarked ultrasound images and their corresponding marked counterparts. Region of interest is cropped from the unmarked images such that the hyperechoic speckles present near the edge regions which simply hinders the contouring are made available to the despeckling process. Filters such as Frost, Lee, Kuan and Wiener with two different window sizes of 3×3 and 5×5 are implemented. Enhanced Lee, Enhanced Frost with 3×3 window size, PMAD filter with 5, 10 and 15 iterations, SBF filter with 5, 10 and 15 iterations are considered for comparison. Performances of the filters are measured quantitatively using MSE, RMSE, SNR, PSNR, SC, UQI and NCC metrics. The images despeckled by these filters are shown in Fig. 1 and 2. Further, the various parameters calculated for these filters are tabulated in Table 2 and 3.

From the careful analysis of the quantitative metrics, following interpretations were made. Lee and Kuan filters

of same window size are giving almost equal results in terms of all quantitative metrics. When the filter window sizes are 5×5 Kuan and Lee seems to be better than Frost in terms of MSE RMSE, SNR and PSNR. Enhanced Lee is good in preserving edges as well as in terms of low MSE, RMSE and high SNR, PSNR when compared to enhanced Frost of same filter window size, but, the UQI is too small. Wiener filter of window size 3X3 seems to be better than 5×5 in terms of SNR, PSNR, MSE and RMSE but gives low SSIM than Wiener of 5×5. The histogram plots of original and despeckled images were very difficult to differentiate visually even though there is a considerable amount of Maximum difference and Average Difference values.

PMAD filter with more number of iterations removes the edges to a greater extent along with the speckle noise. Quantitative metrics as well as the Canny edge map reveals its undesirable property of removing the edges along with the speckle. SBF filters with 5, 10 and 15 iteration seems to exhibit good SSIM. For the PMAD and SBF filters SSIM increases with increase in number of iterations but the MSE and RMSE are high as the number of iterations goes high. When the number of iterations of the SBF filters are set to high such as 50, 100 these filters detect the boundaries well than removing the speckles. For automatic detection of boundary, SBF filters with more number of iterations can be employed. Since it smoothes the region, this cannot be employed for further processing like feature extractions and classifications.

CONCLUSION

In this study an attempt has been made to analyse the quantitative ability of eight speckle filters in despeckling the ultrasound kidney images. Speckle filters have been developed in MATLAB environment and eight performance metrics were used to quantify the performance of the filters. In each filters the parameters such as window size and constants like damping factor, number of iterations were chosen with utmost care Window sizes are limited here as 3×3 and 5×5. For computer aided diagnosis, one can choose filter with little number of constants. Most of the spatial filters are performing well in removing speckles. But the parameters chosen for one image may not suite for another image taken from the same machine and by the same operator. This is because of the scatteres inside the body, organ focussed and the body condition of the patient. For visual inspection by experts little speckle removal may be sufficient. Further studies can be done in optimizing the parameters so that machine dependent, patient dependent issues may be eliminated.

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REFERENCES

Donnel, M.O. and S.D. Silverstein, 1988. Optimum displacement for compound image generation in medical ultrasound. IEEE T. Ultrasonics Ferrelectric Freq. Contr., 35(4): 470-476.

Gonzalez, R.C. and E.W. Richard, 2008. Digital Image Processing. 3rd Edn., Pearson Education, Upper Saddle River, NJ.

Goodman, J.W., 1976. Some fundamental properties of speckle noise. J. Opt. Soc. Am., 66(11): 1145-1150.

Jain, A.K., 1989. Fundamentals of Digital Image Processing. 2nd Edn., Prentice Hall Publication, UK.

Jappreet, K., K. Jasdeep and K. Manpreet, 2011. Survey of despeckling techniques for medical ultrasound images. IJCTA, 2(4): 1003-1007.

Kailath, T., 1976. Equations of Wiener-Hopf Type in Filtering Theory and Related Applications in Norbert Wiener: Collected Works. Masani, P. (Ed.), MIT Press, Cambridge, MA, 3: 63-94.

Kalaivani, N.S. and R.S.D. Wahidabanu, 2009. A view on despeckling in Ultrasound Imaging. IJSPIPPR, 2(9): 85-97.

Lie, P.C. and M.J. Chen, 2002. Strain compounding: A new approach for speckle reduction. IEEE T. Ultrasonics Ferrelectric Freq. Contr., 49(1): 41-44.

Nadia, S., 2006. Speckle reduction in electrocardiographic images. 14th European Signal Processing Conference (EUSIPCO 2006) Proceedings, Florence, Italy.

Raman, M. and A. Himanshu, 2009. Performance evaluation of various filters on medical images. ACEEE Int. J. Recent Trends Eng., 2(4): 22-25.

Sivakumar, R., M.K. Gayathri and D. Nedumaran, 2010. Speckle filtering of ultrasound b-scan images-a comparative study of single scale spatial adaptive filters, multiscale filter and diffusion filters. IACSIT, 2(6): 514-523.

Tay, P.C., C.D. Garson, S.T. Acton and Hossack, 2010. Ultrasound despeckling for contrast enhancement. IEEE T. IP, 19(7): 1847-1860.

Trahey, G.E., J.W. Allison, S.W. Smith and O.T. Von Raman, 1986. A quantitative approach to speckle reduction via frequency compounding. Ultrasonic Imag., 8(3): 151-164.

Wagner, R.F., M.F. Insana, J.M. Sandrik and H. Lopez, 1983. Statistics of speckle in Ultrasound B scans. IEEE T. Sonics Ultrasonics, 30(3): 156-163.

Wagner, R.F., M.F. Insana and S.W. Smith, 1988. Fundamental correlation lengths of coherent speckle in medical ultrasonic images. IEEE T. Ultrasonics Ferroelectric Freq. Contr., 35(1): 34-44.