



Reduction of Speckle Noise from Ultra-Sound Images Using Spatio-Spectral Total Variation Technique

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ABSTRACT:

Ultra-sound (US) is one of the most important imaging technique used in medicine for the diagnosis of internal abnormalities. Due to some phenomenon; noise signals are introduced which is called as speckle noise. Introduction of noise deteriorates the quality of images by suppressing the anatomical information. This information is useful for correct interpretation of US images. Hence it required to remove speckle noise from US images. In this research paper, reduction of speckle noise from US image is done. For this purpose; Spatio-Spectral Total Variation (SSTV) technique is used. To evaluate the performance of de-noising technique three most important parameters have been calculated viz. Power Signal to Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM).

Keywords: Speckle noise, US image, Image De-noising, PSNR, SNR, SSIM.

1. Introduction:

US is one of the most important medical images which is used to diagnose any abnormality or disease in the internal body[1-2]. To take US image; imaging technique is used which uses radio frequency called ultrasound frequency signal[3]. Due to some interference of the signal; noise signal is introduced which appears as patches in the US images[4]. This noise signals are referred as speckle noise[5]. It is multiplicative in nature; i. e. noise signals are direct multiplied to the pixel values of the original images[6-8]. Its Probability Density Function (PDF) follows gamma distribution. Introduction of noise deteriorates the quality of US images; as a result image information is affected; due to which false interpretation may be done by the radiologists[9-12]. Hence it is essential to remove speckle noise from US images. However; it is almost impossible to remove noise from any images completely but it should be reduce to such an extent so that diagnosis purpose must be done properly[10]. Various techniques have been proposed to reduce speckle from images; in which SSTV method give better results among many traditional techniques[13-17]. Fig. 1.1 illustrates some noise free US images taken from the public database.

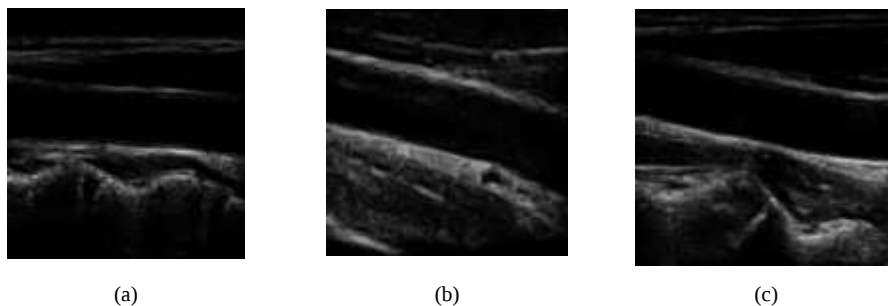


Fig. 1.1 US images

If some amount of speckle is introduced in these images than their quality are deteriorate.

2. Methodology:

In this section; US image de-noising using SSTV method is explained. Below is the description of SSTV technique. Let us consider an image is corrupted by speckle noise. The image acquisition model can be expressed as:

$$y = x + sp \quad \dots(2.1)$$

where, x and y are the original and noisy image respectively and s is the speckle noise.

The SSTV model exploits both spatial and spectral correlation which is given as:

$$SSTV(x) = \|d_h x d\|_1 + \|d_v x d\|_1 \quad \dots(2.2)$$

where d_h and d_v are the horizontal and vertical 2D finite differencing operator.

d is a 1D finite differencing operator.

De-noising problem can be expressed as:

$$\min_{x, n_{sp}} \|y - x - n_{sp}\|_F^2 + \lambda \|n_{sp}\|_1 + \mu SSTV(x) \quad \dots(2.3)$$

where, λ and μ are regularization parameters.

From eq. (2.3)

$$n_{sp} = y - x \quad \dots(2.4)$$

From eq. (2.4) it is clear that the effect of speckle noise can be minimized by minimizing the Frobenius norm of $y-x$.

De-noising algorithm:

From eq. (3.30) and eq. (3.31), de-noising problem can be given as:

$$\min_{x, n_{sp}} \|y - x - n_{sp}\|_F^2 + \lambda \|n_{sp}\|_1 + \mu \|d_h x d\|_1 + \mu \|d_v x d\|_1 \quad \dots(2.5)$$

It is a high dimensional non differentiable optimization problem in x and n_{sp} . Since variable x is non separable hence it can be rewritten into a constrained formulation:

$$\|y - x - n_{sp}\|_F^2 + \lambda \|n_{sp}\|_1 + \mu \|p\|_1 + \mu \|q\|_1 \quad \dots(2.6)$$

where $p = d_h x d$ and $q = d_v x d$

The constrained optimization problem can be expressed in an unconstrained optimization problem using quadratic penalty functions as given below:

$$\text{minimize}_{p, q, x, n_{sp}} \|y - x - n_{sp}\|_F^2 + \lambda \|n_{sp}\|_1 + \mu \|p\|_1 + \mu \|q\|_1 + v \|p - d_h x d\|_F^2 + v \|q - d_v x d\|_F^2 \quad \dots(2.7)$$

where v is the regularization parameter.

Eq. (2.7) has 4 variables (p, q, x, n_{sp}) but now they are separable.

The above problem can be rewritten using Bregman variables B_1 and B_2 as given below:

$$\text{minimize}_{p, q, x, n_{sp}} \|y - x - n_{sp}\|_F^2 + \lambda \|n_{sp}\|_1 + \mu \|p\|_1 + \mu \|q\|_1 + v \|p - d_h x d - B_1\|_F^2 + v \|q - d_v x d - B_2\|_F^2 \quad \dots(2.8)$$

Now, above equation is divided into 4 sub equations:

$$P1: \min_p \mu \|p\|_1 + v \|p - d_h x d - B_1\|_F^2 \quad \dots(2.9)$$

$$P2: \min_q \mu \|q\|_1 + v \|q - d_v x d - B_2\|_F^2 \quad \dots(2.10)$$

$$P3: \min_{n_{sp}} \|y - x - n_{sp}\|_F^2 + \lambda \|n_{sp}\|_1 \quad \dots(2.11)$$

$$P4: \min_x \|y - x - n_{sp}\|_F^2 + v \|p - d_h x d - B_1\|_F^2 + v \|q - d_v x d - B_2\|_F^2 \quad \dots(2.12)$$

$$\arg \min_x \|y - x\|_F^2 + \alpha \|x\|_1$$

The sub problems P_1 , P_2 and P_3 are of the form , which can be solved by using a soft thresholding.

$$\hat{x} = \text{softTh}(y, \alpha) = \text{sgn}(y) \times \max\{0, |y| - \frac{\alpha}{2}\} \quad \dots(2.11)$$

Sub problem P_4 is a least square problem and it can be solved using iterative least square solvers.

Bergman variables B_1 and B_2 can be updated in each iteration as follows:

$$B_1^{K+1} = B_1^k + d_h x d - p \quad \dots(2.12)$$

$$B_2^{K+1} = B_2^k + d_v x d - q \quad \dots(2.13)$$

Fig. 2.1 illustrates the flow diagram of US image de-noising. In this technique; first of all US images are taken from database. This image is noise free. Now some amount of speckle is added in the noise free image; as a result noisy image is obtained. Now SSTV technique is applied which removes the speckle noise from the US images and de-noised image is obtained. De-blurring is done using RL technique. To know the efficacy of SSTV method for de-speckling the US images; some performance evaluation parameters must be calculated. In this paper three most important parameters have been taken viz. PSNR and SSIM[18-20]. Below is the steps of proposed technique in which de-speckling is done using SSTV method[12].

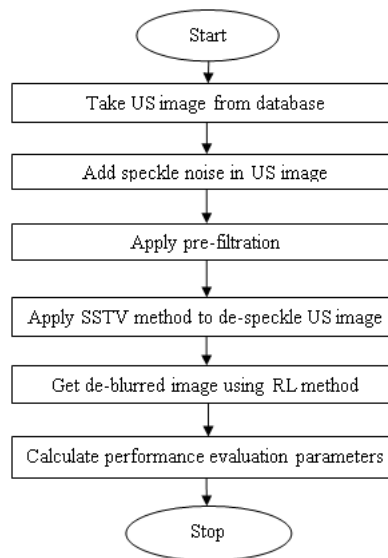


Fig. 2.1 flow diagram of US image de-noising

3. Results & Discussion:

This section contains the results of proposed technique. Results are illustrated in the form of images, calculated parameters values and graphs. Three important parameters have been calculated viz. PSNR and SSIM. Fig 3.1(a) and 3.2(a) are noise free images, fig. 3.1(b) and 3.2(b) are noisy images and 3.1(c) to 3.2(b) are de-noised images of US image 1.

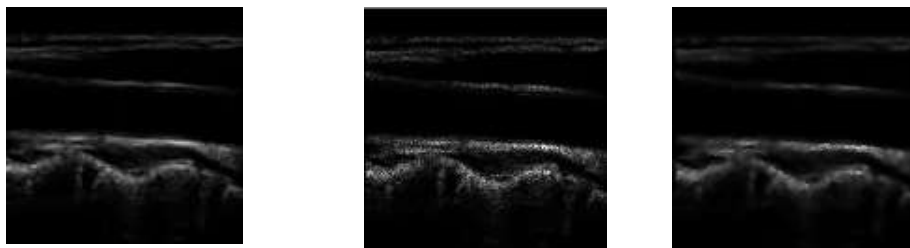


Fig. 3.1 (a) Test image US 1 (b) noisy image with $\sigma_{AWGN}^2=0.01$ (c) de-noised image

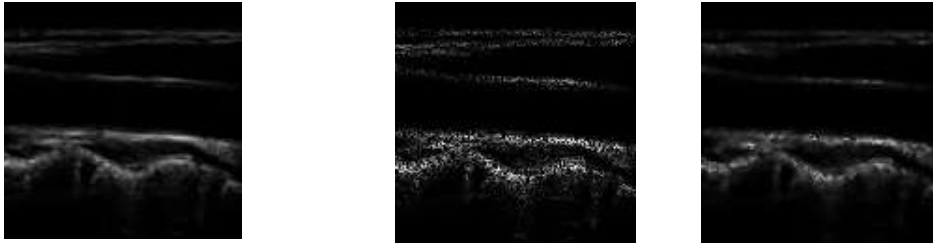
Fig. 3.2 (a) Test image US 1 (b) noisy image with $\sigma_{AWGN}^2=0.5$ (c) de-noised image

Table 3.1 PSNR values for US images for different values of speckle noise

Test Image	PSNR	AWGN Noise Variance (σ_{AWGN}^2)								
		0.01	0.02	0.03	0.04	0.05	0.1	0.2	0.3	0.5
US 1	Noisy PSNR	32.702	32.101	32.112	31.651	31.342	28.711	26.723	25.270	23.144
	Denoised PSNR	38.315	37.812	36.417	36.128	35.973	34.502	33.258	31.507	29.611
US 2	Noisy PSNR	30.735	30.321	30.065	29.243	28.524	26.368	23.312	21.560	19.567
	Denoised PSNR	35.291	34.795	35.112	33.922	33.631	32.219	30.340	28.671	26.331
US 3	Noisy PSNR	33.763	33.146	33.274	32.536	32.323	28.761	26.722	24.871	23.161
	Denoised PSNR	36.976	36.423	35.778	34.817	34.657	32.124	30.315	28.768	27.151

Table 3.2 SSIM values for US test images for different values of AWGN

Test Image	SSIM	AWGN Noise Variance (σ_{AWGN}^2)								
		0.01	0.02	0.03	0.04	0.05	0.1	0.2	0.3	0.5
US 1	Noisy SSIM	0.860	0.819	0.782	0.795	0.745	0.867	0.815	0.782	0.743
	De-noised SSIM	0.976	0.955	0.947	0.926	0.974	0.957	0.953	0.946	0.917
US 2	Noisy SSIM	0.756	0.674	0.629	0.583	0.560	0.756	0.674	0.623	0.564
	De-noised SSIM	0.940	0.911	0.889	0.815	0.823	0.940	0.911	0.887	0.852
US 3	Noisy SSIM	0.743	0.683	0.611	0.587	0.562	0.743	0.684	0.621	0.563
	De-noised SSIM	0.952	0.931	0.923	0.891	0.854	0.951	0.932	0.912	0.875

Plots between noise variance and PSNR and SSIM are plotted for US1 image which are illustrated in fig. 3.3 and 3.4 respectively.

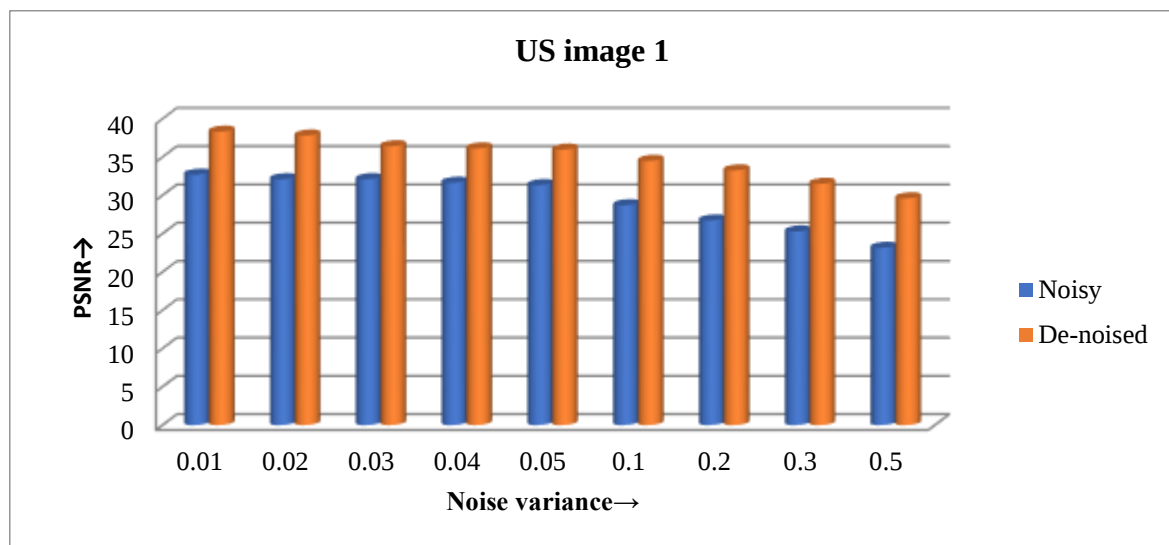


Fig 3.3 PSNR values for noisy and de-noised test image US 1

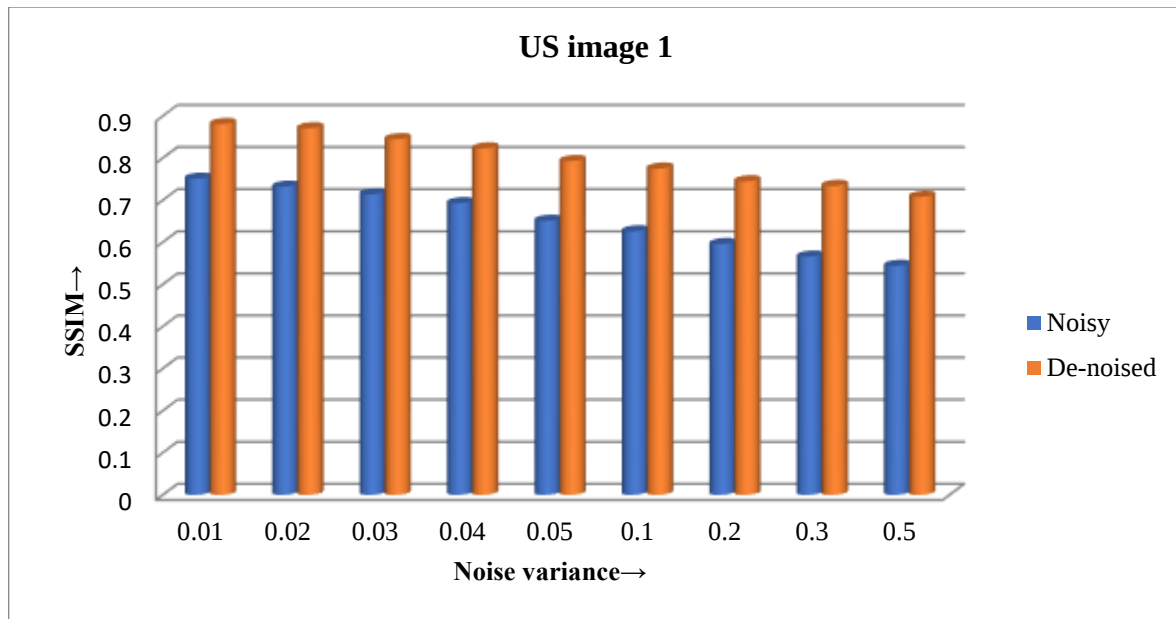


Fig. 3.4 SSIM values for noisy and de-noised test image US 1

From these two graphs it is clear that SSTV technique gives higher PSNR and SSIM values. This technique reduces not only effect of speckle noise but retains image information also.

Conclusion:

From the above discussion and performance evaluation parameters it is clear that; SSTV method suppresses speckle from US images. It also retains image information which is very important feature to diagnose diseases or internal body structures. US images are very useful in medicine for the study of internal organs. Introduction of noise may affect the diagnosis process done by the radiologists. Any misinterpretation may mislead the doctors and further treatments. This technique can be used to de-noise other medical images also but it is important to study about those imaging systems and noise introduced in those images; then only image de-noising may be done by the proposed technique.

References:

1. X. Yu, C. Ge, Z. Fu, M. Z. Aziz and L. Liu, "A two-step filtering mechanism for speckle noise reduction in OCT images," 2021 IEEE 9th International Conference on Information, Communication and Networks (ICICN), Xi'an, China, 2021, pp. 501-505.
2. X. Sang, X. Yu, Z. Yuan and L. Liu, "Speckle Noise Reduction Mechanism Based on Dual-Density Dual-Tree Complex Wavelet in Optical Coherence Tomography," 2020 IEEE 5th Optoelectronics Global Conference (OGC), Shenzhen, China, 2020, pp. 190-192.
3. D. Bhonsle, T. Rizvi, S. Mishra, G. R. Sinha, A. Kumar and V. K. Jain, "Reduction of Ultrasound Images using Combined Bilateral Filter & Median Modified Wiener Filter," 2022 Second International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT), Bhilai, India, 2022, pp. 1-5.
4. Y. Chen *et al.*, "Semi-Supervised Speckle Noise Reduction in OCT Images With UNet and Swin-Uformer," in *IEEE Transactions on Instrumentation and Measurement*, vol. 73, pp. 1-10, 2024, Art no. 4504810.
5. Sivaanpu *et al.*, "Speckle Noise Reduction for Medical Ultrasound Images Using Hybrid CNN-Transformer Network," in *IEEE Access*, vol. 12, pp. 168607-168625, 2024,
6. C. A. Duarte-Salazar, A. E. Castro-Ospina, M. A. Becerra and E. Delgado-Trejos, "Speckle Noise Reduction in Ultrasound Images for Improving the Metrological Evaluation of Biomedical Applications: An Overview," in *IEEE Access*, vol. 8, pp. 15983-15999, 2020.
7. Y. Lan and X. Zhang, "Real-Time Ultrasound Image Despeckling Using Mixed-Attention Mechanism Based Residual UNet," in *IEEE Access*, vol. 8, pp. 195327-195340, 2020.
8. D. Bhonsle, V. K. Chandra, G.R. Sinha, "Noise removal from medical images using shrinkage based enhanced total variation technique", *Journal of Advanced Research in Dynamical and Control System*, vol. 13, pp. 549-560, 2017.
9. G. Khor, G. Ning, X. Zhang and H. Liao, "Ultrasound Speckle Reduction Using Wavelet-Based Generative Adversarial Network," in *IEEE Journal of Biomedical and Health Informatics*, vol. 26, no. 7, pp. 3080-3091, July 2022.

10. D. Bhonsle, V. K. Chandra, G.R. Sinha, "Guassian and Speckle Noise Removal From Ultrasound Images Using Bivariate Shrinkage By Dual Tree Complex Wavelet Transform", *i-manager's Journal on Image Processing*, vol. 2(2), 2015.
11. Y. Qi, Y. Guo and Y. Wang, "Image Quality Enhancement Using a Deep Neural Network for Plane Wave Medical Ultrasound Imaging," in *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 68, no. 4, pp. 926-934, April 2021.
12. D. Bhonsle, G. R. Sinha and D. P. Shrivastava, "Suppression of Gaussian Noise using Spatio-Spectral Total Variation Technique," *2020 Seventh International Conference on Information Technology Trends (ITT)*, Abu Dhabi, United Arab Emirates, 2020, pp. 89-93
13. D. F. Vieira, A. Raposo, A. Azeitona, M. V. Afonso, L. M. Pedro and J. Sanches, "Ultrasound Despeckling With GANs and Cross Modality Transfer Learning," in *IEEE Access*, vol. 12, pp. 45811-45823, 2024.
14. B. Honarvar Shakibaei Asli *et al.*, "Ultrasound Image Filtering and Reconstruction Using DCT/IDCT Filter Structure," in *IEEE Access*, vol. 8, pp. 141342-141357, 2020.
15. D. Bhonsle, "Denoising of Digital Images Using Wavelet-Based Thresholding Techniques: A Comparison," in *Cognitive Behavior and Human Computer Interaction Based on Machine Learning Algorithms*, Wiley, 2022, pp.85-115,
16. M. Sjoerdsma, S. Bouwmeester, P. Houthuizen, F. N. van de Vosse and R. G. P. Lopata, "A Spatial Near-Field Clutter Reduction Filter Preserving Tissue Speckle in Echocardiography," in *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 68, no. 4, pp. 979-992, April 2021.
17. N. Bottenus, M. LeFevre, J. Cleve, A. L. Crowley and G. Trahey, "Resolution and Speckle Reduction in Cardiac Imaging," in *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 68, no. 4, pp. 1131-1143, April 2021.
18. Y. Chang, L. Yan, M. Chen, H. Fang and S. Zhong, "Two-Stage Convolutional Neural Network for Medical Noise Removal via Image Decomposition," in *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 6, pp. 2707-2721, June 2020.
19. D. Bhonsle, V. K. Chandra, G.R. Sinha, "De-Noising Of CT Images Using Combined Bivariate Shrinkage and Enhanced Total Variation Technique.", *i-manager's Journal on Electronics Engineering*, vol. 8(4), 2018.