



Speckle Noise Reduction Using Spatio-Spectral Total Variation Technique

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ABSTRACT:

Ultra-sound (US) is one of the most important imaging techniques 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 is 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), Signal to Noise Ratio (SNR) and Structural Similarity Index Measure (SSIM).

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

Introduction:

US is one of the most important medical images which is used to diagnose any abnormality or disease in the internal body [1-3]. To take US image, imaging technique is used which uses radio frequency called ultrasound frequency signal [4]. Due to some interference of the signal, noise signal is introduced which appears as patches in the US images [5-6]. This noise signal is referred as speckle noise [7]. It is multiplicative in nature; i.e. noise signals are directly multiplied to the pixel values of the original images [8-10]. Its Probability Density Function (PDF) follows gamma distribution [11]. 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 [7]. Hence it is essential to remove speckle noise from US images [12-15]. However, it is almost impossible to remove noise from any images completely but it should be reduced to such an extent so that diagnosis purpose must be done properly [16-18]. Various techniques have been proposed to reduce speckle from images; in which SSTV method gives better results among many traditional techniques [5]. Fig. 1.1 illustrates some noise-free US images taken from the public database.

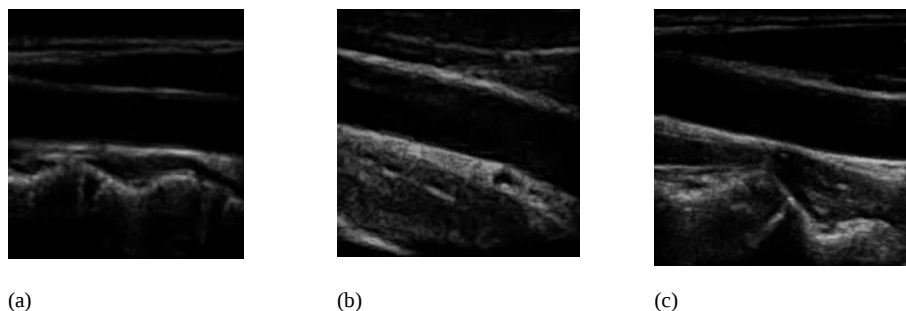


Fig. 1.1 CT images

If some amount of speckle is introduced in these images, their quality deteriorates.

Methodology:

In this section, US image de-noising using SSTV method is explained [19-20].

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:

$$y = x + s \quad \dots(1)$$

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:

$$SSTV(x) = \|d_h x d\|_1 + \|d_v x d\|_1 \quad \dots(2)$$

where d_h and d_v are the horizontal and vertical 2D finite differencing operator and d is a 1D finite differencing operator.

Using SSTV model, de-noising problem can be expressed as:

$$\min_{x, n_{sp}} \|y - x - n_{sp}\|_F^2 + \lambda \|n_{sp}\|_1 + \mu SSTV(x) \quad \dots(3)$$

where, λ and μ are regularization parameters.

From eq. (3.29)

$$g = y - x - n_{sp} \quad \dots(4)$$

From eq. (3.32) it is clear that the effect of Gaussian noise can be minimized by minimizing the Frobenius norm of $y - x - n_{sp}$

De-noising algorithm:

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

$$\min_{x, n_{sp}} \|y - x - n_{sp}\|_F^2 + \lambda \|n_{sp}\|_1 + \mu \|d_h x d\|_1 + \mu \|d_v x d\|_1 \quad \dots(5)$$

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:

$$\|y - x - n_{sp}\|_F^2 + \lambda \|n_{sp}\|_1 + \mu \|p\|_1 + \mu \|q\|_1 \quad \dots(6)$$

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:

$$\text{minimize}_{p, q, x, n_{sp}} \|y - x - n_{sp}\|_F^2 + \lambda \|n_{sp}\|_1 + \mu \|p\|_1 + \mu \|q\|_1 + \nu \|p - d_h x d\|_F^2 + \nu \|q - d_v x d\|_F^2 \quad \dots(7)$$

where ν is the regularization parameter.

Eq. (3.35) 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:

$$\text{minimize}_{p, q, x, n_{sp}} \|y - x - n_{sp}\|_F^2 + \lambda \|n_{sp}\|_1 + \mu \|p\|_1 + \mu \|q\|_1 + \nu \|p - d_h x d - B_1\|_F^2 + \nu \|q - d_v x d - B_2\|_F^2 \quad \dots(3.36)$$

The above problem can be split into four easy sub problems.

$$P1: \min_p \mu \|p\|_1 + \nu \|p - d_h x d - B_1\|_F^2 \quad \dots(8)$$

$$P2: \min_q \mu \|q\|_1 + v \|p - d_v x d - B_2\|_F^2 \quad \dots(9)$$

$$P3: \min_{n_{sp}} \|y - x - n_{sp}\|_F^2 + \lambda \|n_{sp}\|_1 \quad \dots(10)$$

$$P4: \min_x \|y - x - n_{sp}\|_F^2 + v \|p - d_h x d - B_1\|_F^2 + v \|q - d_v x d - B_2\|_F^2 \quad \dots(11)$$

The sub problems $P1, P2, P3$ are of the form $\arg \min_x \|y - x\|_F^2 + \alpha \|x\|_1$, which can be solved by using a soft thresholding.

$$\hat{x} = \text{softTh}(y, \alpha) = \text{sgn}(y) \times \max\{0, |y| - \frac{\alpha}{2}\} \quad \dots(12)$$

Sub problem $P4$ is a least square problem which can be solved using iterative least square solvers. Bergman variables B_1 and B_2 can be updated in each iteration as follows:

$$B_1^{K+1} = B_1^k + d_h x d - p \quad \dots(13)$$

$$B_2^{K+1} = B_2^k + d_v x d - q \quad \dots(14)$$

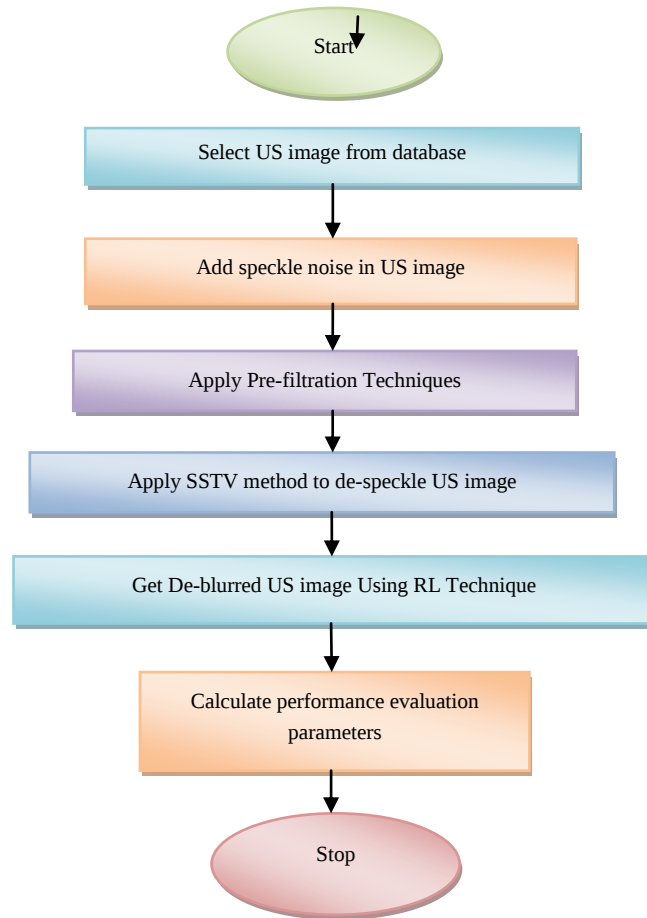


Fig. 3.1 flow diagram of US image de-noising

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. 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.

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 4(a) to 6(a) are noise free images, fig. 4(b) to 6(b) are noisy images and 4(c) to 6(c) are de-noised images of CT image 1, 2 and 3 respectively.

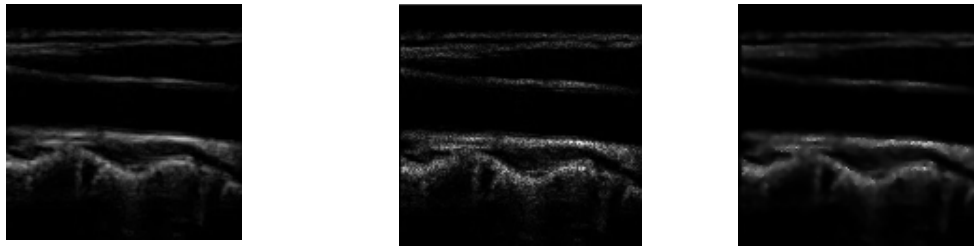


Fig. 4.1 (a) Test image CT 1 (b) noisy image with $\sigma_{AWGN}^2=0.01$ (c) de-noised image

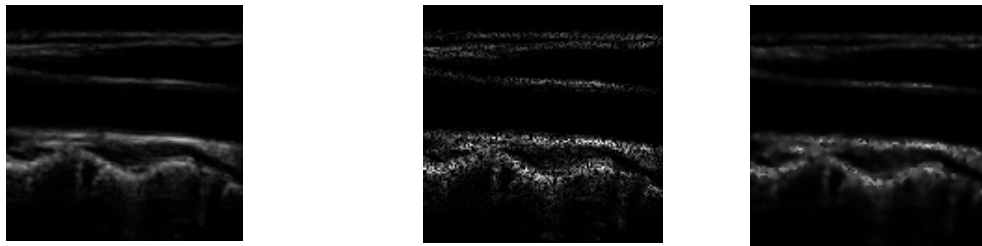


Fig. 4.2 (a) Test image CT 1 (b) noisy image with $\sigma_{AWGN}^2=0.5$ (c) de-noised image

Table 4.1 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	31.004	30.221	29.743	29.102
	Denoised PSNR	37.315	36.812	36.417	36.128	35.973	35.611	35.312	34.918	34.541
US 2	Noisy PSNR	30.735	30.321	30.065	29.243	28.524	28.010	27.338	26.614	26.413
	Denoised PSNR	35.291	34.795	35.112	33.922	33.631	33.027	33.319	32.715	32.483
US 3	Noisy PSNR	33.763	33.146	33.274	32.536	32.323	32.112	31.247	30.866	30.091
	Denoised PSNR	36.976	36.423	35.778	34.817	34.657	34.332	34.012	33.862	33.531

Table 4.2 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	0.731	0.729	0.715	0.778
	De-noised SSIM	0.976	0.955	0.947	0.926	0.974	0.906	0.907	0.893	0.844
US 2	Noisy SSIM	0.756	0.674	0.629	0.583	0.560	0.546	0.526	0.525	0.506
	De-noised SSIM	0.940	0.911	0.889	0.815	0.823	0.841	0.826	0.818	0.811
US 3	Noisy SSIM	0.743	0.683	0.611	0.587	0.562	0.544	0.524	0.525	0.514
	De-noised SSIM	0.952	0.931	0.923	0.891	0.854	0.853	0.8321	0.825	0.834

Plots between noise variance and PSNR and SSIM are plotted for US1 image which are illustrated in fig. 4 and 6 respectively.

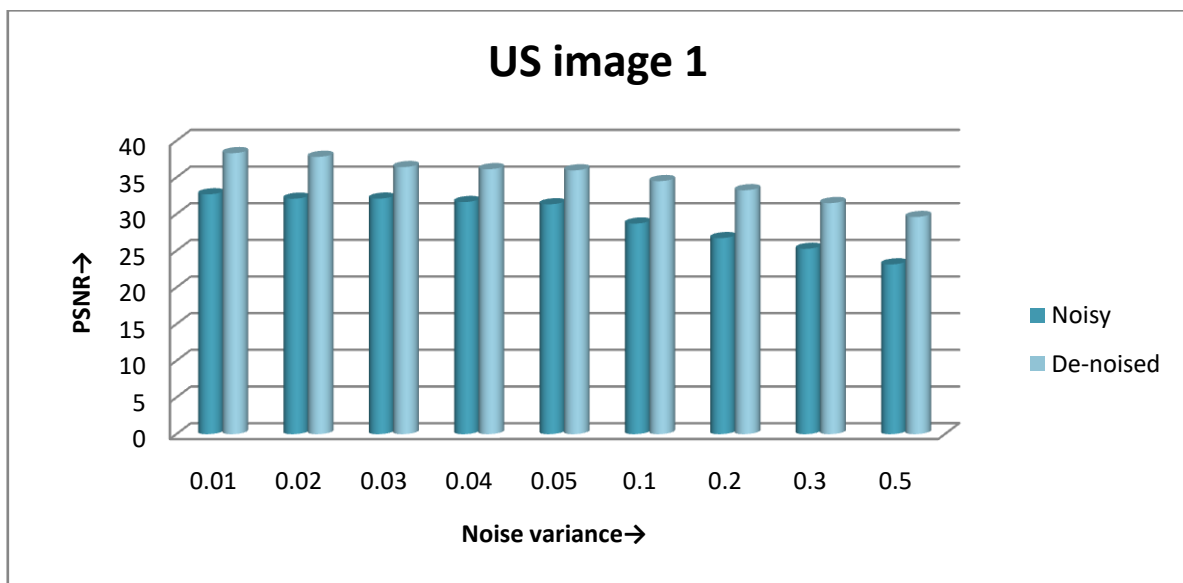


Fig 4.4 PSNR values for noisy and de-noised test image US 1

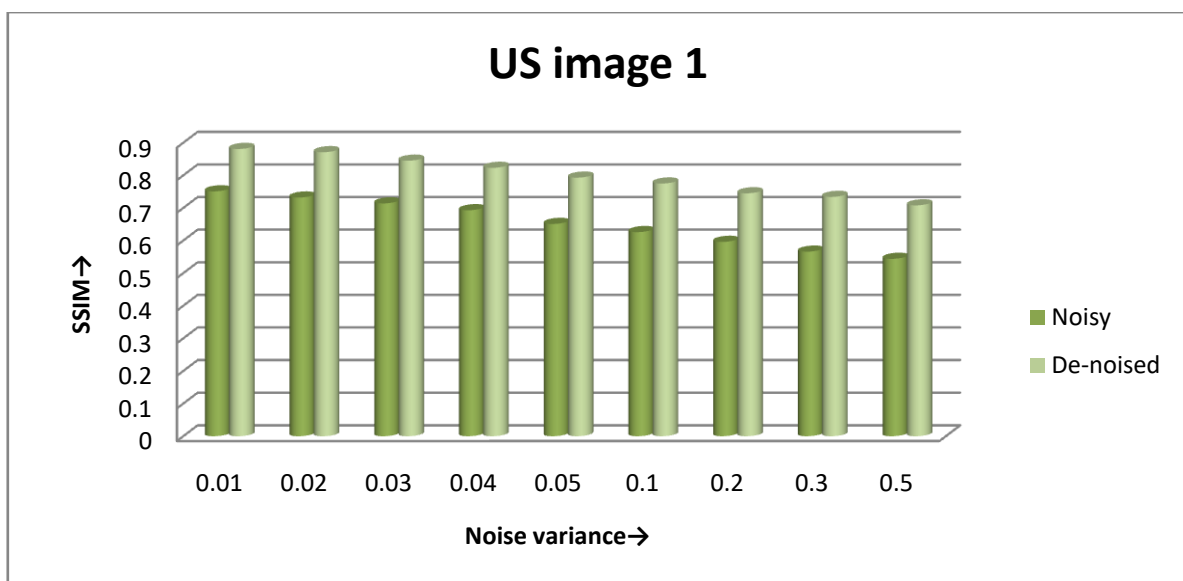


Fig. 4.5 SSIM values for noisy and de-noised test image US 1

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 abovediscussion 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.

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