Comparative Analysis of Speckle Noise Reducing Algorithms with Various Novelties

R. Suganya
Department of CSE,
Thiagarajar College of Engineering,
Madurai - 625015,
TamilNadu,India.

P. Shalini
Department of CSE,
Thiagarajar College of Engineering,
Madurai- 625015.
TamilNadu,India.

S. Rajaram
Department of CSE,
Thiagarajar College of Engineering,
Madurai-625015,
TamilNadu,India.

ABSTRACT
This work provides the knowledge about adaptive and anisotropic diffusion techniques for speckle noise removal from various types of ultrasonic liver images. A comparative study is made based on the performance of various algorithm such as anisotropic, speckle reducing anisotropic diffusion algorithm(SRAD), Laplacian pyramid non-linear diffusion (LPND) with various filters like Gaussian, Sobel, Average, Disk, Unsharp and log. Finally a fused algorithm is developed which performs all the filtering techniques on the input image and the statistical parameters are calculated for the output images obtained from all the filters.

Key words
Speckle noise, Ultrasonic, SRAD, and LPND.

1. INTRODUCTION
Each imaging system suffers with a common problem of "Noise". Unwanted data which may reduce the contrast deteriorating the shape or size of objects in the image and blurring of edges or dilution of fine details in the image may be termed as noise.

Mathematically there are two basic models of Noise; additive and multiplicative. Additive noise is systematic in nature and can be easily modeled and hence removed or reduced easily. Whereas multiplicative noise is image dependent, complex to model and hence difficult to reduce. When multiplicative noise caused by the de-phased echoes from the scatters appears, it is called "Speckle Noise". Although it appears as noise but it contains useful information because it is due to surroundings of the target.

Speckle is the result of the diffuse scattering, which occurs when a sound wave (RF sound or Ultrasound) pulse randomly interferes with the small particles or objects on a scale comparable to the sound wavelength. In most cases, it is considered a contaminating factor that severely degrades image quality. Most speckle filters are developed for enhancing visualization of speckle images. Medical imaging like Ultrasound is very popular due to its low cost, least harmful to human body, real time view and small size [1] and [2]. Filter analysis has been done to select the best filter for a given image on the basis of some statistical parameters. Finally we designed the fused method which has various combinations of filters to give a better outcome.

1.1 Detailed Design

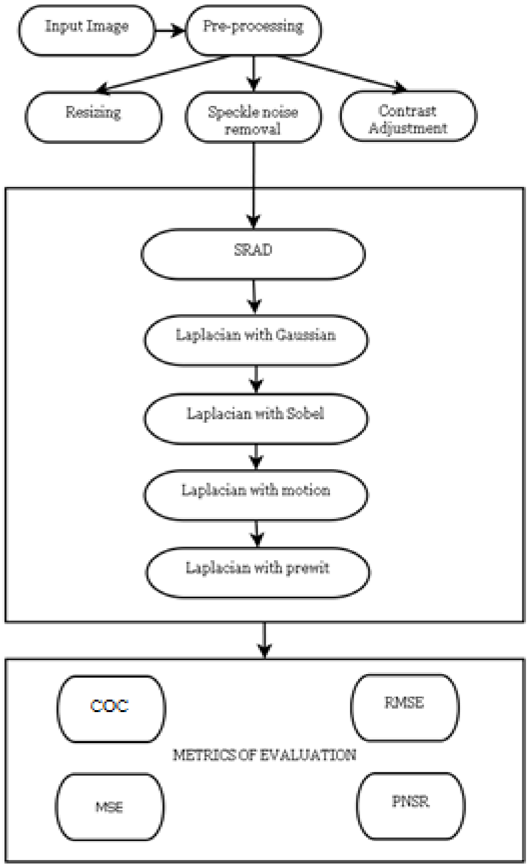

Fig 1: Detailed design of proposed method with metrics of evaluation

2. SPECKLE NOISE IN ULTRASOUND IMAGES
An ultrasound-based diagnostic medical imaging technique used to visualize muscles and many internal organs, their size, structure and any pathological injuries with real-time tomography images. It is also used to visualize a fetus during routine and emergency prenatal care. Obstetric sonography is commonly used during pregnancy. It is one of the most widely used diagnostic tools in modern medicine. The technology is relatively inexpensive and portable, especially when compared with other imaging techniques such as magnetic resonance imaging (MRI) and computed tomography (CT). Speckle noise affects all coherent imaging systems including medical ultrasound. Within each resolution

cell a number of elementary scatters reflect the incident wave towards the sensor. The backscattered coherent waves with different phases undergo a constructive or a destructive interference in a random manner. The acquired image is thus corrupted by a random granular pattern, called speckle that delays the interpretation of the image content.

In the medical literature, speckle noise is referred as "texture", and may possibly contain useful diagnostic information. The desired grade of speckle smoothing preferably depends on the specialist's knowledge and on the application. Physicians generally have a preference of the original noisy images more willingly than the smoothed versions because the filters even if they are more sophisticated can destroy some relevant image details [2]. Thus it is essential to develop noise filters which can secure the conservation of those features that are of interest to the physician.

2.1 Major Causes of Speckle Noise

Due to incorrect assumption the ultrasound pulse always travel in a straight line, to and fro from the reflecting interference. Another source of reverberations is that a small portion of the returning sound pulse may be reflected back into the tissues by the transducer surface itself, and generates a new echo at twice the depth [5]. Speckle is the result of the diffuse scattering, which occurs when an ultrasound pulse randomly interferes with the small particles or objects on a scale comparable to the sound wavelength. The backscattered echoes from irresolvable random tissue in homogeneities in ultrasound imaging and from objects in Radar imaging undergo constructive and destructive interferences resulting in mottled b-scan image.

2.1.1 Need for filtering

Speckle degrades the quality of US images and thereby reducing the ability of a human observer to discriminate the fine details of diagnostic examination. This artifact introduces fine-false structures whose apparent resolution is beyond the capabilities of imaging system, reducing image contrast and masking the real boundaries of the tissue leading to the decrease in the efficiency of further image processing such as edge detection and automatic segmentation [6].

3. ANISOTROPIC DIFFUSION

In image processing and computer vision, anisotropic diffusion, also called Perona–Malik diffusion, is a technique aiming at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image. Anisotropic diffusion resembles the process that creates a scale-space, where an image generates a parameterized family of successively more and more blurred images based on a diffusion process. Anisotropic diffusion is a generalization of this diffusion process it produces a family of parameterized images, but each resulting image is a combination between the original image and a filter that depends on the local content of the original image. As a consequence, anisotropic diffusion is a non-linear and space-variant transformation of the original image. The mathematical formula is as the following [3],

Formally, let $\Omega \subset \mathbb{R}^2$ denote a subset of the plane then anisotropic diffusion is defined as,

$$\frac{\partial I}{\partial t} = div(c(x,y,t)\nabla I) = \nabla c.\nabla I + c(x,y,t)\nabla I$$

Where,

∇ Denotes the gradient,

div(…) is the divergence operator and

c(x,y,t) is the diffusion coefficient.

c(x,y,t) Controls the rate of diffusion and is usually chosen as a function of the image gradient so as to preserve edges in the image. Pietro Perona and Jitendra Malik pioneered the idea of anisotropic diffusion and proposed two functions for the diffusion coefficient [4]:

$$c(\| \nabla I \|) = e^{-\left(\frac{\|\nabla I\|}{K}\right)^2}$$

$$c(\| \nabla I \|) = \frac{1}{1 + \left(\frac{\|\nabla I\|}{K}\right)^2}$$

And the constant K controls the sensitivity to edges and is usually chosen experimentally or as a function of the noise in the image.

3.1 SRAD

SRAD (Speckle Reducing Anisotropic Diffusion) [4]-[5] is a diffusion method for ultrasonic and radar imaging applications based on partial differential equations (PDEs). It is used to remove locally correlated noise, known as speckles, without destroying important image features. SRAD consists of several pieces of work: image extraction, continuous iterations over the image (preparation, reduction, statistics, computation 1 and computation 2) and image compression. The sequential dependency between all of these stages requires synchronization after each stage (because each stage operates on the entire image). The SRAD has the advantage of

a. One less independent parameter [7],

b. Less dependence on the norm of the gradient which can vary in the image,

c. A natural decrease of the diffusion as the estimated standard deviation of the noise decreases:

3.2 Gaussian Filter

Gaussian filters are designed to give no overshoot to a step function input while minimizing the rise and fall time. This behavior is closely connected to the fact that the Gaussian filter has the minimum possible group delay. Mathematically, a Gaussian filter modifies the input signal by convolution with a Gaussian function; this transformation is also known as the Weierstrass transform [8].

$$g(x,y) = \frac{1}{2\pi\sigma^2} e^{(-x^2+y^2)/2\sigma^2}$$

Where *x* is the distance from the origin in the horizontal axis, *y* is the distance from the origin in the vertical axis, and *σ* is the standard deviation of the Gaussian distribution.

3.3 Laplacian Filter

The Laplacian L(x,y) of an image with pixel intensity values I(x,y) is given by:

$$\mathbf{L(x,y) = (\delta^2 I / \delta^2 x) + (\delta^2 I / \delta^2 x)}$$

This can be calculated using a convolution filter. Since the input image is represented as a set of discrete pixels, we have to find a discrete convolution kernel that can approximate the second derivatives in the definition of the laplacian [8].

3.3.1 Log

The Laplacian is a 2-D isotropic measure of the 2nd partial derivative of an image. The Laplacian is often applied to an image that has first been smoothed with something approximating a Gaussian smoothing filter in order to reduce its sensitivity to noise, and hence the two variants will be described together here. The operator normally takes a single gray level image as input and produces another gray level image as output [9]. The Laplacian *L(x,y)* of an image with pixel intensity values *I(x,y)* is given;

$$L(x,y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2}$$

The Laplacian can be calculated using standard convolution methods. Doing things this way has two advantages:

a. Since both the Gaussian and the Laplacian kernels are usually much smaller than the image, this method usually requires far fewer arithmetic operations.

b. The LoG (`Laplacian of Gaussian') kernel can be recalculated in advance so only one convolution needs to be performed at run-time on the image.

4. FUSED METHOD

The fused method is a sequential process. The output of one phase acts as the input of the next phase. SRAD is adaptive and does not utilize hard thresholds to alter performance in homogeneous regions or in regions near edges and small features. The output of this filter is fed into another filter called the median filter. Consequently, for each pixel calculate its laplacian value with different filters- Gaussian, sobel, motion and prewrit. The output of this fused method reduces more speckles noises compare to other conventional approaches.

5. METRICS OF EVAUATION

5.1 Mean Square Error

In statistics, the mean squared error (MSE) of an estimator is to quantify the difference between values implied by an estimator and the true values of the quantity being estimated [10]. The MSE of an estimator $\hat{\theta}$ with respect to the estimated parameter θ is defined as,

$$MSE(\hat{\theta}) = E[(\hat{\theta} - \theta)^2]$$

The MSE is equal to the sum of the variance and the squared bias of the estimator.

$$MSE(\hat{\theta}) = Var(\hat{\theta}) + (Bias(\hat{\theta},\theta))^2$$

Table 1. Comparative analysis of liver images with the MSE values of various speckle noise removal methods

Image	Normal	Fatty	Cirrhosis	Cyst
SRAD	49.501	16.2487	20.9765	25.9766
Average	105.5094	37.4558	49.5967	44.7208
Sobel	236.5879	101.026	134.4821	169.9372
Log	234.0677	102.7856	134.5368	173.0742
Unsharp	75.6452	37.5034	49.6644	44.8865
Disk	55.4347	37.4853	49.6043	44.7006
Gaussian	47.5211	21.3819	27.8392	31.1951
Fused	14.6703	16.067	19.1356	25.3521

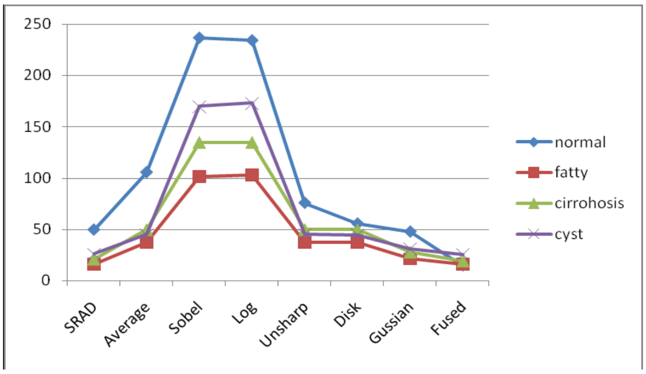

Fig 2: Comparative analysis of MSE with various speckle reduction methods

5.2 Peak Signal to Noise Ratio (PSNR)

The PSNR is defined in logarithmic scale, in dB. It is the ratio of peak signal power to noise power [11].

$$PSNR = 10 \log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

$$= 20 \log_{10}(MAX_I) - 10 \log_{10} MSE$$

Table 2. Comparative analysis of liver images with the PSNR values of various speckle noise removal methods

Image	Normal	Fatty	Cirrhosis	Cyst
SRAD	72.0453	72.0453	67.98	69.8269
Average	64.7912	64.7912	63.2514	53.6883
Sobel	56.1729	56.1729	51.6558	53.6848
Log	56.023	72.1429	51.497	62.3407
Unsharp	64.7802	64.7802	63.2193	62.2512
Disk	64.7844	64.7844	63.2553	67.3685
Gaussian	69.6607	69.6607	66.3799	67.36216
Fused	72.1429	56.023	68.1813	70.6248

5.3 RMSE

The root-mean-square deviation (RMSD) or root-mean-square error (RMSE) is a frequently used measure of the differences between values predicted by a model or an estimator and the values actually observed.

The RMSD of an estimator $\hat{\theta}$ with respect to the estimated parameter is $\hat{\theta}$ defined as the square root of the mean square error:

$$RMSD(\hat{\theta}) = \sqrt{MSE(\hat{\theta})} = \sqrt{E\left((\hat{\theta} - \theta)^2\right)}$$

For an unbiased estimator, the RMSD is the square root of the variance, known as the standard error.

Table 3. Comparative analysis of liver images with the RMSE values of various speckle noise removal methods

Image	Normal	Fatty	Cirrhosis	Cyst
SRAD	4.031	4.311	5.0938	4.58
Average	6.1201	6.6768	6.6874	7.425
Sobel	10.0512	10.6823	13.036	11.5966
Log	10.1383	10.6728	13.1558	11.599
Unsharp	6.124	6.6823	6.6997	7.0473
Disk	6.1225	6.6788	6.6859	5.273
Gaussian	4.6241	4.993	5.5853	4.3744
Fused	4.0084	4.2657	5.0351	4.3744

5.4 CoC

The Correlation of Coefficient is a method that employs tracking and image registration techniques and it allows to accurately estimating changes into images. It estimates the similarity between the original and demonized images [12]. The CoC between two imagesA_{mn} and B_{mn} Is:

$$r = \frac{(\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B}))}{\sqrt{(\sum_m \sum_n (A_{mn} - \overline{A^2})(B_{mn} - \overline{B^2}))}}$$

where A and B are average or mean of image matrix elements

Table 4. Comparative analysis of liver images with the CoC values of various speckle noise removal methods

Image	Normal	Fatty	Cirrhosis	Cyst
SRAD	0.9222	0.9518	0.7419	0.967
Average	0.7221	0.6223	0.0688	0.7386
Sobel	0.1636	0.174	0.0596	0.151
Log	0.791	0.655	0.7414	0.0578
Unsharp	0.7212	0.6213	0.7416	0.738
Disk	0.7221	0.6223	0.7416	0.7384
Gaussian	0.8378	0.7431	0.9064	0.8414
Fused	0.9899	0.9722	0.9457	0.8952

Figure 2 has shown the comparison of speckle reduction by fused method with various above said algorithms.

Fig 2: Comparison of Speckle Reduction by fused method and various speckle reduction methods

6. CONCLUSION

From the above analysis, it is clear that, the fused method reduces the speckle noise more effectively than other conventional methods. The MSE value must be the least value for the images. Comparing with all the algorithms the fused method gives the least MSE value. PSNR value must be greater than the original images value. More the PSNR value more noise is reduced. PSNR value is greater in fused method. similarly RMSE and COC has shown better result compare to other existing methods. Thus the comparative study of various speckle noise reducing algorithms with various metrics of evaluation has been done and the new fused method is also show to be better than the existing algorithms.

7. REFERENCES

[1] Zhang, F., Yoo, Y. M., Koh, L. M., & Kim, Y. 2007. Nonlinear diffusion in laplacian pyramid domain for ultrasonic speckle reduction. Medical Imaging, IEEE Transactions on, 26(2), 200-211.

[2] Hope, T., Gregson, P., Linney, N., & Schmidt, M. 2004, Augus). Ultrasonic tissue characterization as a predictor of white matter damage: results of a preliminary study. In Ultrasonics Symposium, 2004 IEEE (Vol. 3, pp. 2157-2160). IEEE.

[3] Burt, P., & Adelson, E. 1983. The Laplacian pyramid as a compact image code. Communications, IEEE Transactions on, 31(4), 532-540.

[4] Yu, J., Tan, J., & Wang, Y. 2010. Ultrasound speckle reduction by a SUSAN-controlled anisotropic diffusion method. Pattern Recognition, 43(9), 3083-3092.

[5] Arun, K. S., Huang, T. S., & Blostein, S. D. 1987. Least-squares fitting of two 3-D point sets. Pattern Analysis and Machine Intelligence, IEEE Transactions on, (5), 698-700.

[6] San diego.F 2 006. Robust registration of 3-D ultrasound images based on Gabor filter and mean-shift method. Computer vision and mathematical methods in medical and biomedical image analysis, 3117, 304–316.

[7] Djemal, K. 2005, September. Speckle reduction in ultrasound images by minimization of total variation. In Image Processing, 2005. ICIP 2005. IEEE International Conference on (Vol. 3, pp. III-357). IEEE.

[8] Acton, S. T. 2005, September. Deconvolutional speckle reducing anisotropic diffusion. In Image Processing, 2005. ICIP 2005. IEEE International Conference on (Vol. 1, pp. I-5). IEEE.

[9] Tyna Hope, Peter Gregson, Norma LinneyAnd Matthias Schmidt. 2009. Ultrasonic Tissue Characterization As A Predictor Of White Matter Damage: Results Of A Preliminary Study. IEEE International Ultrasonic, Ferroelectrics, And Frequency Control Joint 50th Anniversary Conference.

[10] Yu, Y., Molloy, J. A., & Acton, S. T. 2004, June. Generalized speckle reducing anisotropic diffusion for ultrasound imagery. In Computer-Based Medical Systems, 2004. CBMS 2004. Proceedings. 17th IEEE Symposium on(pp. 279-284). IEEE.

[11] Zhou Wang, Alan Conrad Bovik, Hamid Rahim Sheikh and Eero P. Simoncelli,"Image Quality Assessment: From Error Visibility to Structural Similarity", IEEE Transactions on Image Processing, vol.13, pages: 600-612. 2007.

[12] Mastriani, M., & Giraldez, A. 2004. Enhanced directional smoothing algorithm for edge-preserving smoothing of synthetic-aperture radar images. Journal of Measurement Science Review, 4(3), 1-11.