A Novel Weighted Diffusion Filtering Approach for Speckle Suppression in Ultrasound Images

Vikrant Bhateja, Gopal Singh, and Atul Srivastava

Dept. of Electronics & Communication Engg., SRMGPC, Lucknow-227105 (U.P.), India
{bhateja.vikrant,gopal.singh13492,atul.srivastava216}@gmail.com

Abstract. Ultrasound images mainly suffer from speckle noise which makes it difficult to differentiate between small details and noise. Conventional anisotropic diffusion approaches tend to provide edge sensitive diffusion for speckle suppression. This paper proposes a novel approach for removal of speckle along with due smoothening of irregularities present in the ultrasound images by modifying the diffusion coefficient in anisotropic diffusion approach. The present work proposes a diffusion coefficient which is a function of difference of instantaneous coefficient (of variation) and the coefficient of variation for homogeneous region. The finally reconstructed image is obtained by weighted addition of the response of proposed anisotropic diffusion filter and the Laplacian filtered image. Simulation results show that performance of the proposed approach is significantly improved in comparison to recently developed anisotropic diffusion filters for speckle suppression.

Keywords: Anisotropic diffusion, Speckle suppression, Laplacian, Instantaneous coefficient of variation.

1 Introduction

In the near past, ultrasound imaging has emerged as the gold standard for doctors and radiologists for the detection of cysts (both benign and malignant) and cancerous tumors. This is because of its several advantages over other imaging modalities. It is non-invasive, harmless, and efficient in terms of cost and accuracy [1]. However, ultrasound images are contaminated with an inherent noise called 'speckle' which tends to have a granular effect on the image, thereby degrading its visual quality [2]. For simplifying the therapeutic decision making and diagnosis, the ultrasound images should have minimum amount of noise. This calls for the development of speckle filtering techniques over past decades. The conventional methods for speckle reduction include the Lee filtering [3] and Kuan filtering [4]. In Lee filtering, the multiplicative speckle noise is converted into additive noise before filtering. In Kuan filter, the filtering action varies according to the image statistics based on non stationary mean and variance image model. In progression, techniques involving anisotropic diffusion [5] were proposed employing variable diffusion coefficient. The first work in this domain was Perona-Malik anisotropic diffusion (PMAD) filter [6] in which a variable coefficient of diffusion was used in the standard scale-space

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paradigm so that it has a larger value in the homogeneous regions. Detail-Preserving Anisotropic Diffusion (DPAD) [7] is based on the extension of Frost's and Kuan's linear minimum mean square error filters used for a multiplicative noise. The Speckle-Reducing Anisotropic Diffusion (SRAD) [8] is based on the partial differential equations (PDE). Oriented Speckle-Reducing Anisotropic Diffusion (OSRAD) [9] is a technique in which a vector is associated with the SRAD filter to achieve directional filtering. Ramp-Preserving Perona-Malik model (RPPM) [10] makes the use of a diffusion coefficient chosen to avoid the staircasing effect and preserve edges. You-Kaveh's models (YKM) [11] approximates the noisy image with a piecewise planar image. The Adaptive Window Anisotropic Diffusion [12] exploits a variable size and orientation window. The work of A. Gupta *et al.* [13-15] was based on the despeckling of SAR images and the work of A. Jain *et al.* [16-18] dealt with denoising of the mixture of different noises in medical images. All the above mentioned approaches perform well. However, limitations like edge blurring, over-smoothing and greater number of iterations are present. Hence, the proposed work aims to reduce the complexity, provide better filtering and develop a computationally efficient approach by using the diffusion process without performing multiple iterations. The performance is shown under section of results and discussions. The paper is structured as follows: in Section 2, the novel diffusion filtering approach is proposed. Section 3 presents the results and discussions and in Section 4, the paper has been concluded.

2 Proposed Diffusion Filtering Approach

The diffusion filtering techniques have proved to be superior over conventional techniques in terms of their speckle suppression ability, feature preservation and edge enhancement. These techniques make the use of fundamental anisotropic diffusion equation given by Perona and Malik [5] stated as:

$$I_t = c\Delta I + \nabla c . \nabla I \tag{1}$$

where: I is the input ultrasound image, c is the conduction or diffusion coefficient, ∇ is the gradient operator and Δ is the Laplacian operator. By the judicious choice of parameter c, the diffusion process can be controlled. The aim is to make the diffusion coefficient approach unity in the interior of homogeneous region (to enhance diffusion in this region) and zero at the boundaries (to stop diffusion at boundaries avoiding blurring). However, problems like staircasing effect and blurring have encouraged the researchers to develop better approaches. This has led to the evolution of better performing diffusion coefficients. In this context, the SRAD filtering approach [8] uses the diffusion coefficient as a function of local gradient magnitude and Laplacian operators for edge preservation. In this proposed filtering approach, a modified diffusion coefficient has been presented to improve the performance of SRAD filters. The new diffusion coefficient is a non linear function of coefficient of variations. If $p(x,y)$ denotes the instantaneous coefficient of variation and $p_o(x,y)$ denotes the instantaneous coefficient of variation in the homogeneous region, then the diffusion coefficient proposed in this work can be stated as:

$$c(p) = \frac{1}{\sqrt{1+(p-p_o)^n}} \tag{2}$$

where: n denotes the power index raised to the difference of coefficients of variation. Significant improvement in speckle suppression can be attained by approximating the value of n to be greater than 3. The coefficient p can be mathematically represented as:

$$p = \sqrt{\frac{Var(I_{i,j})}{\bar{I}_{i,j}^{\;2}}} = \sqrt{\frac{\frac{1}{4}\sum_{q=1}^{4}(I_q - \bar{I}_{i,j})^2}{\bar{I}_{i,j}^{\;2}}} \tag{3}$$

where: $\bar{I}_{i,j} = \frac{1}{4}\sum_{q=1}^{4} I_q$ is the average intensity of a pixel considering the four nearest neighborhood pixels. Coefficient p_0 is given by:

$$p_o = \left(\frac{R}{\sqrt{2}}\right) MAD\left(\| \nabla \log I_{i,j}^{\,t} \|\right) \tag{4}$$

MAD(.) is called the median absolute deviation, $\| \; \|$ and $| \; |$ are the magnitude of gradient and the absolute value respectively. R is a constant whose value is 1.4826 [19]. The modified diffusion coefficient leads to improved isotropic diffusion in homogeneous regions of the ultrasound images (speckled). The instantaneous coefficient of variation therefore evaluates to larger values on high contrast regions and lower values on homogeneous regions. Hence, in homogeneous regions p is taken close to p_0 to make $c(p)$ approach unity and for the edges, the value of p is large so that $c(p)$ is made as low as possible. Diffusion filtering approaches are implemented using multiple iterations of diffusion equation which at times to the computational load and also degrades the quality of reconstructed image. Further, the present work addresses this issue by weighted addition of filtered response in the manner suggested. The first step involves speckle filtering using (1)-(4). The reconstructed image obtained is then denoted as I_1. Secondly, another image is generated which is composed of the noisy image added to its weighted Laplacian given by (5):

$$L(I) = a.c\left(\| \nabla I \|\right)\Delta I \tag{5}$$

where: a is a constant whose value is less than unity. Its lower value ensures that the edges are preserved. The inhomogeneous weight $c\left(\| \nabla I \|\right)$ is used to reduce diffusion near edges. When this weighted Laplacian is added to the image, smoothed output image is obtained. This image I_2 is given by:

$$I_2 = I + L(I) \tag{6}$$

The finally reconstructed image I_{final} is obtained by weighted addition of two images I_1 and I_2 generated in the first and second step. This is shown mathematically as:

$$I_{final} = K_1.I_1 + K_2.I_2 \tag{7}$$

where: K_1 and K_2 are the weights for the images whose values are to be determined experimentally based on the values of evaluation parameters.

3 Results and Discussions

3.1 Evaluation Parameters

Two state-of-art evaluation parameters Peak Signal-to-Noise Ratio (*PSNR*) [21] and the Structural Similarity Index (*SSIM*) [20] are used for performance evaluation. The higher value of *PSNR* denotes the better quality of reconstructed ultrasound image. The luminance, contrast and structural similarity functions are combined to generate Structural Similarity (*SSIM*) Index. Its value ranges from zero to unity where the value zero corresponds to zero structural similarity and unity represents exact similarity. Mathematically, it is given as:

$$SSIM = \left(\frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2}\right) \cdot \left(\frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}\right) \cdot \left(\frac{2\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3}\right) \tag{8}$$

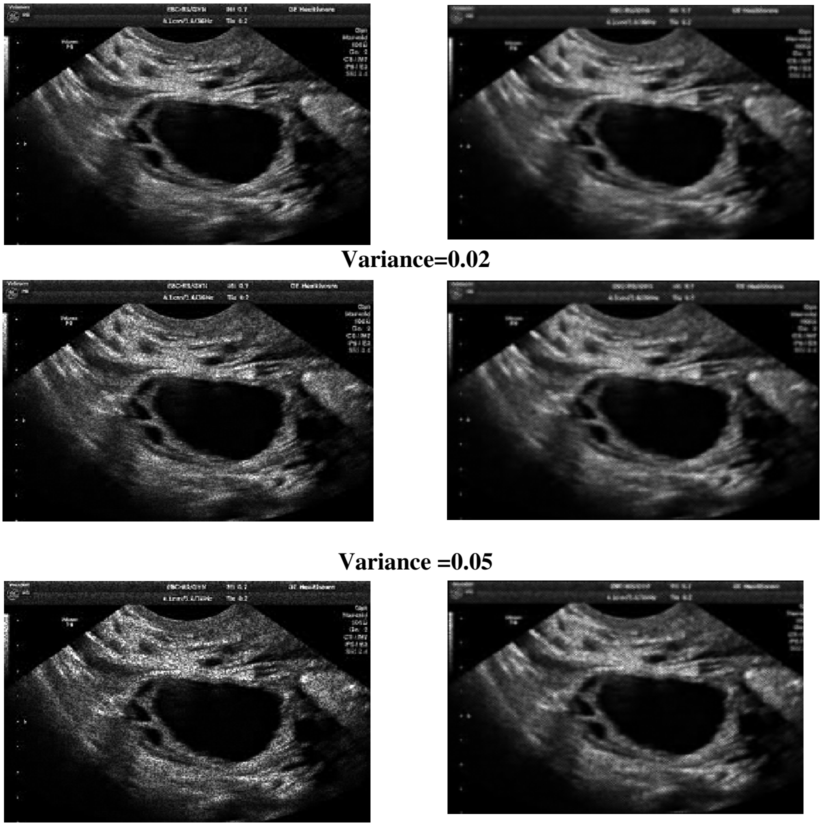
where: μ_x and μ_y are the mean values of images x and y, σ_x and σ_y are the local standard deviations while σ_{xy} is the cross correlation of x and y after removing the mean. The values of parameters C_1, C_2 and C_3 in this equation are taken in accordance with [20]. The performance of the proposed approach has also been evaluated based on Coefficient of Correlation (*CoC*) which can show the similarity between actual and expected results. *CoC* can be given by:

$$CoC = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu_x)(y_i - \mu_y) \tag{9}$$

where: x_i and y_i are the i^{th} samples in the images x and y and N is the total number of pixels. The value of *CoC* approaching unity denotes better preservation of features between the input and output ultrasound images. Image quality assessment measures those used above and some proposed recently [22]-[27] can be used for evaluation of speckle suppression algorithms.

3.2 Simulated Results

The input ultrasound images for this experiment are taken from [28]. In the simulation process, (1)-(4) and (5)-(6) are used to generate the first and second image respectively, as described in the previous section. Then, (7) is used to generate the final reconstructed image. Finally, (8)-(9) are used for performance evaluation of the proposed model. The value of n in (2) is taken 4 and a in (5) is taken 0.3. In (4), it is clear that p_o uses the logarithm of the input ultrasound image. So, in order to avoid a mathematical error which may occur for the pixel with a value 0, a negligibly small value is added to every pixel (which has almost no effect on the visibility). To avoid over-enhancement and over-smoothing, in (7) $K_1+K_2=1$ is satisfied. Also to ensure that speckle is removed as much as possible $K_1>K_2$ is also ensured. In this experiment, values taken are $K_1=0.8$ and $K_2=0.2$ as these values produced the better edge preservation and smoothing. Figure 1 shows the images which have been corrupted by the speckle noise of different variances and the denoised images by the proposed approach.



Variance=0.02

Variance =0.05

Variance= 0.10

(a) **(b)**

Fig. 1. (a) Noisy images at various noise variances (b) Corresponding speckle suppressed images

It can be seen that the level of speckle is considerably reduced and the visualization of the ultrasound images is also improved to a great extent in the reconstructed images. It also shows that while the speckle noise is increasing, the performance of the approach is still able to preserve the details of the image and is not found to be ineffective at larger amount of noise. Table 1 shows the performance of proposed approach in terms of various performance evaluation metrics described earlier. The values of performance parameters are obtained at various noise variances in increasing order from 0.00 to 0.10.

Table 1. Performance Evaluation of Proposed Speckle Filtering Approach at Different Noise Variances for Images in Fig.1

Noise Variance	SSIM	CoC	PSNR (in dB)
0.00	0.9764	0.9680	27.1052
0.01	0.9750	0.9656	25.7898
0.02	0.9734	0.9630	24.8098
0.03	0.9718	0.9607	23.9323
0.04	0.9708	0.9588	23.2691
0.05	0.9688	0.9557	22.6148
0.08	0.9645	0.9496	21.3690
0.10	0.9619	0.9453	20.6450

It is clear from the table that the proposed method maintains a high degree of correlation and *SSIM* for increasing noise variance. For low noise variances like 0.01-0.05, the value for *CoC* is as high as 0.968-0.958 showing high correlation between the output ultrasound image and the speckle-free image. At high noise variance, the performance is even more commendable. *CoC* of around 0.95 is considered to be appreciable at such high noise. The *SSIM* index shows that at low noise variance, more than 97% of the structural features are preserved and it drops very slowly to 96.2% for 0.10 noise variance, still a very good value of *SSIM*. The *PSNR* does not drop drastically with increasing noise densities. It can be seen that as the noise variance is increased from 0.00 to 0.10, the *PSNR* only undergoes a total change of around 6.5 dB. The performance of this approach was found better in terms of complexity in implementation, evaluation parameters and number of iterations. In the work of G. Liu *et at.* [12], the *SSIM* index for the model was around 0.65 after 60 iterations. The proposed approach produces high *SSIM* equivalent to 0.97 without using further iterations. In the other models shown, SRAD had a *SSIM* of 0.35, Anisotropic Wiener filter had *SSIM* 0.5 and DPAD had *SSIM* of 0.35 after 60 iterations. The OSRAD method produced its best *SSIM* of 0.47 at 2-3 iterations but it was still less from the proposed model. All these results show that the proposed approach can be very helpful in denoising the ultrasound images and simplifying the work of radiologists and doctors in reading the images for computer-aided detection of breast cancer [29].

4 Conclusion

Speckle is the major undesirable artifact (noise) present inherently in the ultrasound images. Its removal from these images is an important and complicated process needed for further processing. In this paper, a novel approach is presented which makes the use of a novel diffusion coefficient and in-homogeneously weighted

Laplacian to generate the reconstructed image. The parameters used are determined experimentally and those which provide better results are chosen. The visibility of features of the ultrasound image is highly improved and over-enhancement of intensities and over-smoothing has also been taken care of. The method is efficient and produces fruitful results without performing large number of iterations. Future possibilities in this method are the improvements in the approach based on the textural features of the ultrasound image.

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