IJRCCT International Journal of Research in Computer & Communication Technology ISSN 2278-5841

A New Filtering Technique for denoising Speckle Noise from Medical Images Based on Adaptive and Anisotropic Diffusion Filter

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Abstract— This is a preliminary study and the objective of this study has been to compare the performance of some of the primitive and fundamentally different post acquisition image enhancement algorithms as applied to different ultrasound (US) images. Such a comparison would help to decide as to which algorithm could be useful for clinicians, and in evaluating the role of different US images enhancement in a soft-copy environment. In this study, 3 types of US images (**Liver, kidney & Abdomen**) were taken, and 5 fundamentally different and widely employed image enhancement techniques were applied on these images. As the principal objective of image enhancement is to obtain an image with a high content of visual detail, a multipoint rank-order method was used to identify small differences or trends in observations. Among the different algorithms, the proposed modified anisotropic diffusion filtering outperformed than other techniques.

Index Terms—**Medical Image, CT Image, MRI Image, Anisotropic Diffusion, Adaptive Filter, Enhancement.**

1. INTRODUCTION

Ultrasound imaging 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 **MRI** and **Computed Tomography (CT)**. Medical images are usually corrupted by noise during their acquisition and transmission. The main objective of image de-noising technique is to remove such noises while retaining as much as the important signal features. Introductory section offers brief idea about different available de-noising scheme. Ultrasound imaging is a widely used medical imaging procedure, because it is economical, comparatively safe, transferable and adaptable. One of its main shortcomings is the poor quality of images, which are affected by speckle noise. The existence of speckle is unattractive since it disgraces the image quality and affects the task of individual interpretation and diagnosis. Accordingly, the speckle filtering is a central pre-processing step for feature extraction, analysis and recognition from medical imagery measurements.

2. METHODOLOGY

An appropriate method for speckle reduction is one which enhances the signal-to-noise ratio while conserving the edges and lines in the image [1]-[2]. Adaptive filters generally incorporate the **Kaun filter**, **Lee filter**, **Frost filter**. These filters exploited the local statistical properties of the image and so performed better in comparison to lowpass filters. Adaptive filters perform much better than lowpass smoothing filters, in preservation of the image sharpness and details while suppressing the speckle noise.

3. IMAGE NOISE

There are different types of noise by which medical ultrasound images can be affected. Such that impulse noise, Gaussian noise, Random noise, speckle noise etc.

4. SPECKLE NOISE MODEL

Consider an original image Y corrupted by the Multiplicative noise . The resultant distorted image X, may be written as [1][3][17].

$$X(i,j) = h(i,j)*Y(i,j) + n(i,j) ;$$

Where h(i,j) denotes the point spread function (PSF) and n (i,j) additive noise.

5. ADAPTIVE FILTER

The adaptive mean filters have been proposed in order to reduce blurring in the smoothing process. They adapt to the properties of the image locally and remove speckles from the image. The local image statistics such as mean, variance and spatial correlation are used by these filters to effectively detect, preserve edges and features. The standard adaptive mean filters for speckle reductions are Lee, Kuan and Frost.

5.1 Kuan and Lee filter

The Lee and Kuan filters produce the enhancement data [2][8][10][12] according to

$$\hat{R}(t) = \overline{I}(t) + [I(t) - \overline{I}(t)] \times W(t)$$

W is the weighting function ranging between 0 for flat regions and 1 for regions with high signal activity $\overline{I}$, is the average of pixels in a moving window and R(i,j) is the output of the filter. The weighting function for the Lee filter[2][3][8][12] is calculated

$$W(t) = 1 - \frac{C_u^2}{C_I^2(t)}$$

Where $C_u = \frac{\sigma_u}{\overline{u}}$ and $C_I = \frac{\sigma_I}{\overline{I}}$ are the coefficients of variations of the noise u and the image I. The weighting function of the kuan filter [2][8][10] is defined as

$$W(t) = \frac{1 - C_u^2 / C_I^2(t)}{1 + C_u^2}$$

From the equations the difference between the two filters is only the term $1+C_u^2$. In the homogeneous regions $C_u^2 = C_I^2$ and the value of W approaches 0, which makes the filter to act like a mean filter. In the areas of high variance like edges, $C_I^2 = \infty$, and the value of W approaches 1, which tends to preserve the originally observed image, which makes the filters to act like an all pass filter.

5.2 Frost filter

Frost filter [2][3][11] is a spatial domain adaptive Wiener filter that is based on the multiplicative noise model and uses the local statistics. The image $Z[i, j]$ is modeled by frost[3]as

$$Z_{i,j} = [X_{i,j} \cdot n_{i,j}] * h_{i,j}$$

Where $h\ i\ j$, is system impulse response and * denotes convolution. Minimum mean square filter has
Where $t = (i, j)$ is the spatial coordinate. The ***m(t)*** function is an isotropic impulse response of the spatial filter[3] chosen to minimize

$$\hat{x}(t) = z(t) * m(t)$$

$$J = E[\hat{x}(t) - x(t)]^2$$

It is given by the expression[3][11]:

$$m(t) = K_1 \alpha \exp(-\alpha t)$$

K_1 is a normalizing constant and α is the decay constant given [3][11] by:

$$\alpha^2 = \frac{2a}{\sigma_n^2}\left[\frac{\sigma_x^2}{\sigma_x^2 + \overline{z}^2}\right]$$

Where ***a*** the correlation coefficient between adjacent pixels of the original is image ***x(t)*** and *t* corresponds to the distance between pixels in the spatial domain.

5.3 Anisotropic Diffusion filter

Anisotropic diffusion [2][5]-[8][13]-[16] is a powerful image enhancer and restorer based on the PDE of heat transfer. Anisotropic diffusion is known to smooth the signal, preserve strong edges, enhance the contrast of edges. In image processing and computer vision, anisotropic diffusion, also called Perona–Malik diffusion[5]-[7], 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 [9]. Formally, let $\Omega \subset R^2$ denote a subset of the plane and $I(.,t) : \Omega \to R$ be a family of gray scale images, then anisotropic diffusion[2][5]-[8][13]-[16] is defined as

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

Where Δ denotes the Laplacian, ∇ 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[5]-[7] in 1990 and proposed two functions for the diffusion coefficient:

$$c(\|\nabla I\|) = \exp\left[-(\|\nabla I\| / k)^2\right]$$

$$c(\|\nabla I\|) = \frac{1}{1 + (\|\nabla I\| / k)^2}$$

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

6. PROPOSED METHOD

Algorithm:

1. Input image with or without speckle noise
2. Choose a kernel or window of size 5*5 or 3*3.
3. Set the kernel or window to the noisy image and replace each pixel value of image by the following equation

$$W_n[1:F] = I_0[1:MN]$$
$$I_{sort} = sort(W_n)$$
$$I_{mid} = mid(I_{sort})$$

4. Calculate gradient in all directions (N,S,E,W) of Processed image I_{mid}.

5. Calculate Diffusion coefficients in all directions according to the method using proposed modified equation.

$$C(\|\Delta I_{mid}\|) = \sqrt{\frac{1}{1+\left(\frac{\|\Delta I_{mid}\|}{K}\right)^{2}}}$$

6. Finally follow the following equation

.

$$I_{out} = I_0 + I_{mid} + \lambda \times \begin{bmatrix} c\left(\left|\nabla_{North} I_{mid}\right|\right)\cdot \nabla_{North} I_{mid} + \\ c\left(\left|\nabla_{East} I_{mid}\right|\right)\cdot \nabla_{East} I_{mid} \\ + c\left(\left|\nabla_{West} I_{mid}\right|\right)\cdot \nabla_{West} I_{mid} + \\ c\left(\left|\nabla_{South} I_{mid}\right|\right)\cdot \nabla_{South} I_{mid} \end{bmatrix}$$

7. EXPRIMENT & RESULT

In the experimentation, there have used various ultrasound images. The performance of the system that has been designed and implemented in MATLAB.

TABLE 1: Comparison Table

Filter Name		Image Name	SNR		RMSE	PSNR	IMGQI	SSIM	PT
			Original	Output					
Lee		Abdomen	13.10	12.41	0.07	97.72	0.59	1.00	1.78 e-004
		Liver_GB	12.39	11.06	0.07	98.04	0.37	0.98	8.50 e-004
		Kidney	12.11	10.98	0.08	98.20	0.47	0.99	0.001
Kuan		Abdomen	13.10	12.44	0.07	97.73	0.69	1.00	0.003
		Liver_GB	12.39	11.25	0.07	98.05	0.49	1.00	0.003
		Kidney	12.11	11.17	0.08	98.24	0.59	1.00	0.002
Frost		Abdomen	13.10	5.05	0.06	97.72	0.83	1.00	0.001
		Liver_GB	12.39	3.98	0.07	98.05	0.67	1.00	0.002
		Kidney	12.11	4.83	0.06	98.23	0.77	1.00	0.002
AD	PM 1	Abdomen	13.10	12.67	0.05	97.72	0.87	1.00	0.002
		Liver_GB	12.39	11.27	0.05	98.05	0.76	1.00	0.002
		Kidney	12.11	11.50	0.05	99.22	0.85	1.00	0.001
	PM 2	Abdomen	13.10	9.68	0.03	97.72	0.87	1.00	0.004
		Liver_GB	12.39	8.78	0.04	98.05	0.75	1.00	0.002
		Kidney	12.11	8.62	0.03	99.22	0.84	1.00	0.003
Proposed Modified Filter		Abdomen	13.10	12.75	0.13	97.72	1.00	1.00	0
		Liver_GB	12.39	11.45	0.14	98.06	1.00	1.00	0
		Kidney	12.11	11.24	0.17	98.25	1.00	1.00	0

Visual Comparision:

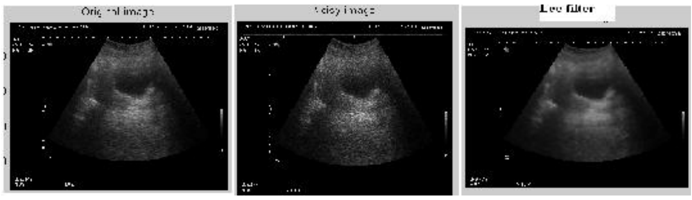

Figure 1: Input and Output of Abdomen Image for Lee Filter.

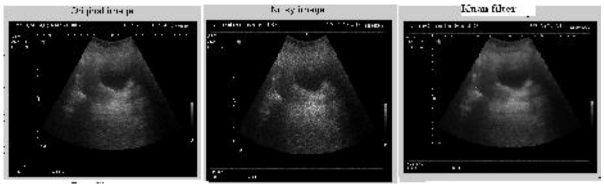

Figure 2: Input and Output of Abdomen Image for Kuan Filter.

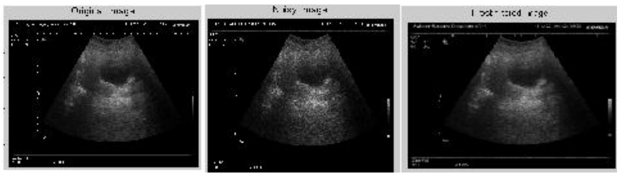

Figure 3: Input and Output of Abdomen Image for Frost Filter.

Figure 4: Input and Output of Liver_GB Image for Lee Filter.

Figure 5: Input and Output of Liver_GB Image for Kuan Filter.

Figure 6: Input and Output of Liver_GB Image for Frost Filter.

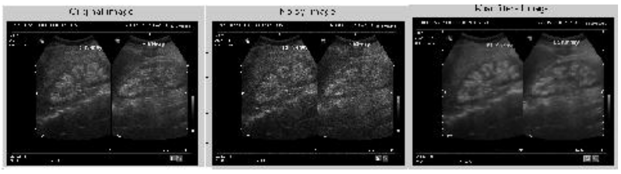

Figure 7: Input and Output of Kidney Image for Lee

ISSN(Online) 2278-5841
ISSN (Print) 2320-5156

Filter.

Figure 8: Input and Output of Kidney Image for Kuan Filter.

Figure 9: Input and Output of Kidney Image for Frost Filter.

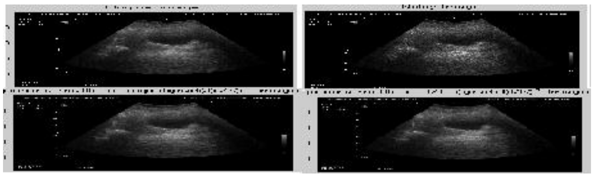

Figure 10: Input and Output of Abdomen Image for Anisotropic Diffusion Filter.

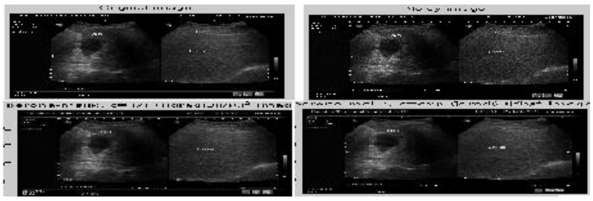

Figure 11: Input and Output of Liver_GB Image for Anisotropic Diffusion Filter.

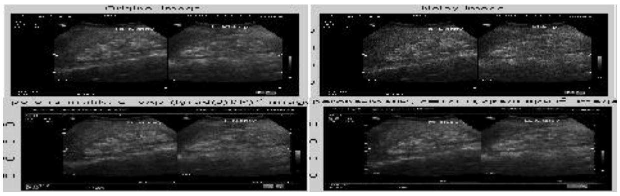

Figure 12: Input and Output of Kidney Image for Anisotropic Diffusion Filter.

Figure 13: Output of Proposed Filter a) Abdomen, b) Liver_GB, c) Kidney Image.

7. CONCLUTION

Although the resulting family of images can be described as a combination among the original images and filtered images. From table we can see that the proposed modified filter gives better **SNR, IMGQI, SSIM, PT, RMSE value** for all 3 (Abdomen, Liver_GB, Kidney) types of US images.

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