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Implementation of Proposed Despeckling Algorithm in Spatial Domain

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Abstract* — *Mostly the images captured through coherence illumination are formed with higher level of speckle noise. The success ratio of segmentation after the preprocessing of the image that involves denoising depends on the extent of the removal of noise from the image. In the preprocessing stage, the noise present in the medical image has to be removed while preserving the edge information and other structural details of the image. This research is focused on design of algorithms for speckle denoising of Ultra Sound images and Optical Coherence Tomography images in spatial domain. Standard speckle filters in spatial domain were analyzed and compared with the proposed method. Results obtained proved that the proposed method performed better than the existing spatial domain filters in denoising and preserving the edge details.

Key Words: *Speckle noise, Coherence image, adaptive lee filter, Edge preservation, Image metrics.*

1. INTRODUCTION

Medical images are usually corrupted by noise during acquisition and transmission. The main objective of image restoration is to remove the noise as much as possible and at the same time important features of the image must be retained. Diagnosis of the captured image becomes difficult due to the distortion of visual signals. These distortions are termed as 'Speckle Noise'. Speckle noise occurs in almost all coherent imaging systems such as laser, acoustics and SAR imagery and because of this noise the image resolution and contrast are reduced, hence reducing the accurate diagnostic of the imaging modality[1]. So, reducing the speckle noise is the first step in coherent medical images. A tradeoff between noise reduction and retaining the features of the image should be made to improve the interpretation of the image.

The image restoration techniques are based on mathematical and statistical models of image degradation. Denoising methods are problem specific and depends upon the corresponding noise model of an image. The noise removal technique has to be chosen depending on the level of quality degradation of the image. Several techniques are proposed for image de-noising and each technique has its advantages and disadvantages. There are two types of denoising techniques: spatial domain filtering and transform domain filtering[2]. Spatial domain filters are further classified as linear filters and non-linear filters. The linear filters perform simple filtering, but it ignores the regional structure and the resulting image often appears blurry and diffused. This undesirable effect is reduced by non-linear filtering techniques, in which local structures and statistics are taken into account during the process of filtering.

2. REVIEW OF LITERATURE

J.S. Lee et al[3] proposed an edge preserving filter. The outcome of the Lee filter is almost equal to the local signal mean in the flat parts of the signal. But in the rapidly varying parts of signal, the output of the Lee filtering is almost equal to the observed signal value.

Jingdong et al[4] stated that Wiener filter is able to preserve edges and other high-frequency information in the image. It estimates the original data with minimum mean-squared error and hence, the overall noise power in the filtered output is minimal.

P.Perona et al[5] developed anisotropic diffusion a powerful filter where local image variation is measured at every point, and pixel values are averaged from neighborhoods whose size and shape depend on local variation. Diffusion methods average over extended regions by solving partial differential equations, and are therefore inherently iterative.

John A Hossack et al[6] extended the 2D speckle reduction technique (SRAD) to 3D. Its performance was considered superior to other conventional filters in terms of smoothing uniform regions and preserving edges and features.

Shin Min Chao et al[7] proposed Detail Preserving Anisotropic Diffusion Filter (DPAD). The filter was able to preserve edges and fine details by including local gradient and gray-level variance and at the same time it was able to remove the noise. But the filter cannot be applied to the images that contain impulse noise because such type of noise contains higher gray-level variance and gradient than the edges and fine details.

Wang et al [8]proposed a new class of fractional-order anisotropic diffusion equations for image denoising. It is a generalization of second-order and fourth-order anisotropic diffusion equations.

Rudin et al[9] proposed total variation (TV) filter which is also iterative in nature. The total variation of the image is minimized subjected to constraints involving the statistics of the noise. The constraints are imposed using Lagrange multipliers.

Tomasi et al[10] proposed bilateral filter which was simple and non-iterative for edge preserving and smoothing. It combines gray levels or colors based on both geometric closeness and photometric similarity, and prefers near values to distant values in both domain and range.

Buades et al proposed non local means filter, which averages similar image pixels defined according to their local intensity similarity.

2.1 Review Findings

- Low-pass filters smoothes the whole image, regardless of the local effect of noise. As they do not distinguish between noise and information in high-frequencies, low-pass filters blurs the fine details in the image regardless of the valuable information[11].
- Ordered statistics filter affects the image uniformly, regardless of the local effect of noise. It often creates artifacts in the image, especially around fine details and it is strongly influenced by the sample size (i.e. window size)[12].
- Linear filters tend to blur sharp edges, destroy lines and other fine image details, and perform poorly in the presence of signal-dependent noise[13].
- With non-linear filters, the noise is removed without any attempts to explicitly identify it. Generally spatial filters remove noise to a reasonable extent but at the cost of blurring images which in turn makes the edges in pictures invisible[14].
- Statistical filters available for speckle reduction are, Mean, Kuan, Frost and Lee filter etc. Results show that statistical filters are good in speckle reduction but they also lose important feature details. Additionally prior knowledge about noise statistics is a prerequisite for statistical filters[15].
- Spatial domain filters also causes the small and less contrast lesions to disappear along with the noise, which will affect the direct use of them in enhancing the medical images for diagnostic purpose[16].

3. MATHEMATICAL MODEL OF SPECKLE NOISE

Speckle Noise is multiplicative in nature. This type of noise is an inherent property of coherent imaging. It affects the diagnostic value of imaging modality, because of reduced image resolution and image contrast. So, speckle noise reduction is an essential preprocessing step, in coherent medical images. Mathematically, the speckle noise is represented with the help of these equations below:

$$g(x,y) = f(x,y) * u(x,y) + \xi(x,y) \quad (1)$$

Where, $g(x,y)$ is the observed image, $u(x,y)$ is the multiplicative component and $\xi(n,m)$ is the additive component of the speckle noise. Here 'x' and 'y' denotes the radial and angular indices of the image samples. As in coherent imaging, only multiplicative component of the noise is to be considered and additive component of the noise has to be ignored[17]. Hence, equation (1) can be modified as;

$$g(x,y) = f(x,y) * u(x,y) + \xi(x,y) - \xi(x,y) \quad (2)$$

Therefore,

$$g(x,y) = f(x,y) * u(x,y) \quad (3)$$

4. PROBLEM FORMULATION

The proposed work is targeted to remove speckle noise while retaining as much as possible important signal features, enhancing edges without changing features, and to provide a good visual appearance. For medical images often Low Peak Signal to Noise Ratio (PSNR), High Root Mean Square Error (RMSE) and Low Edge Preservative Factor (EPF) are obtained. But if the PSNR is too small or the contrast too low it becomes very difficult to detect anatomical structures because tissue characterization fails. Hence for a visual analysis of medical images, the clarity of details and the object visibility are important, so high PSNR, low RMSE & and high EPF are required.

4.1 Development of Adaptive Lee Filter

An Adaptive Lee Filter (ALF) is developed for suppressing speckle noise by estimating the noise σ_n, using inter-quartile range, a robust estimate of the spread of the noise. An adaptive window size of 3*3 is selected, if the estimated noise σ_n is less than or equal to 10. A window size 5*5 is selected, if the estimated noise σ_n is between 10 and 30 and window size 7*7 is selected, if the estimated noise is above 30. This filter is a modified version of lee filter where the size of the window varies with the level of complexity of a particular region in an image and the noise power as well. A smooth or flat region (also called as homogenous region) is said to be less complex as compared to an edge region. The region containing edges and textures are treated as highly complex regions. The window size is increased for a smoother region and also for an image with high noise power.

The work begins by estimating the level of speckle noise present in the input image. Inter Quartile Range (IQR)[18] is used as a robust measure to estimate the noise present in the image. The size of the window is determined based on the noise estimation. The window size is made larger in smooth regions and is kept smaller in the regions where edges are located. In order to estimate a noiseless pixel in a particular region from a noisy image, more number of pixels in the neighborhood surrounding the noisy pixels are required. As correlation is more in homogenous region, a larger sized window is considered if the pixel to be filtered belongs to a homogenous region[19]. On the other hand, smaller-sized window is used if the neighboring pixels are less correlated and belongs to a non-homogenous region or the edge region.

However, a little bit of noise will still remain in the non-homogenous or edge region even after filtration. But human eye is not so sensitive to noise in any edge region. Hence, a variable sized window may be a right choice for efficient image denoising. In the proposed adaptive window lee filter, the window is made adaptive i.e. the size of the window varies from region to region. Sigma and the similarity index are calculated within each window and finally the filtered image f(x,y) is obtained and the filtered image is evaluated with the assessment parameters mentioned in section V.

4.2 Algorithm for Adaptive Lee Filter.

Step-1: Read the noisy image I(x,y)

Step-2: Estimate the noise

$$\sigma_n = 0.7413 * \sqrt{IQR(I_{(x,y)})}$$

Step-3: Determine the window_size

i) If (σ_n <10), then a window of size [3*3] is selected for filtering the noisy pixels belonging to homogenous regions.

ii) If (10<σ_n<30) then a window of size [5*5] is selected for filtering the noisy pixels belonging to flat regions.

iii) If (σ_n> 30) then the size of the window is [7*7].

Step-4: Calculate sigma = $\frac{\sqrt{(I_{(x,y)}-mean)^2}}{window\_size^2}$ to obtain the pixel of interest.

Step-5: Calculate the similarity index $SI = \left(\frac{sigma}{mean}\right)^2$

Step-6: Filtered image is obtained using

$$F_{(x,y)} = mean - \frac{(I_{(x,y)} + mean^2)}{SI}$$

Step-7: The filtered image is evaluated using various performance metrics like PSNR, RMSE, IQI, SSIM, NMV, NSD, ENL, DR, FOM, CC.

Step-8: Stop

5. IMAGE METRICS

5.1 Peak Signal to Noise Ratio

Peak Signal to Noise Ratio (PSNR)[20] is one of the most essential statistical parameter for quality measurement of an image or signal. It is used as an estimate to measure the quality of objective difference between the noisy and the denoised image. The basic idea is to compute a single number that reflects the quality of the reconstructed image. Higher PSNR value provides higher image quality. It is calculated as;

$$PSNR = 10 * log10\left(\frac{1}{MSE}\right) \quad (4)$$

5.2 Root Mean Square Error

Root Mean Square Error (RMSE) [21], is an estimator in to quantify the amount by which a noisy image differs from noiseless image. RMSE is computed by averaging the squared intensity of the noisy image and the denoised image, where error is the difference between desire quantity and estimated quantity. Having a RMSE value of zero is ideal.

$$RMSE = \sqrt{\frac{\sum_{x=1}^{m}\sum_{y=1}^{n}\left(\hat{f}(x,y) - f(x,y)\right)^2}{m*n}} \quad (5)$$

5.3 Image Quality Index

The Image Quality Index (IQI)[20] is a measure of comparison between original and distorted image. It is divided into three parts: luminance $l(x,y)$, contrast $c(x,y)$, and structural comparisons $s(x,y)$ as mentioned in equation (6),(7) and (8). The dynamic range for *IOI(x, y)* is [-1, 1].

$$l(x,y) = \frac{2\mu_x\mu_y}{\mu_x^2 + \mu_y^2} \quad (6)$$

$$c(x,y) = \frac{2\,\sigma_x\,\sigma_y}{\sigma_x^2+\sigma_y^2} \quad (7)$$

$$s(x,y) = \frac{2\sigma_{xy}}{\sigma_x+\sigma_y} \quad (8)$$

$$IQI(x,y) = l(x,y).c(x,y).s(x,y) = \frac{4\mu_x\mu_y\mu_{xy}}{(\mu_x^2+\mu_y^2)(\sigma_x^2+\sigma_y^2)} \quad (9)$$

5.4 Structural Similarity Index

The Structural Similarity Index (SSIM) [20] measures the similarity between two images which is more consistent with human perception than conventional techniques. The range of values for the SSIM lies between −1, for a bad and 1 for a good similarity between the original and despeckled images, respectively.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y+c1)(2\sigma_{xy}+c2)}{(\mu_x^2+\mu_y^2+c1)(\sigma_x^2+\sigma_y^2+c2)} \quad (10)$$

5.5 Noise Mean Value (NMV), Noise Standard Deviation (NSD)

Noise Variance determines the contents of the speckle in an image[22]. A lower variance gives a “cleaner” image as more speckle is reduced, it is not necessarily that it should depend on the intensity of the image. The formulas for the NMV and NSD calculation are as follows.

$$NMV = \frac{\sum_{r,c} f_d(r,c)}{r*c} \quad (11)$$

$$NSD = \sqrt{\frac{\sum_{r,c}(f_d(r,c)-NMV)^2}{r*c}} \quad (12)$$

5.6 Pratt’s Figure of Merit (FOM)

It measures edge pixel displacement between each filtered image I_{filt} and the original image I_{orig}. It is defined as[23]:

$$FOM = \frac{1}{\max(N_{filt}, N_{orig})} \sum_{i=1}^{n} \frac{1}{1+d_i^2\alpha}$$

(13)

where N_{filt} and N_{orig} are the number edge pixels in edge maps of I_{filt} and I_{orig}. Parameter α is set to a constant 1/9, and d_i is the euclidean distance between the detected edge pixel and the nearest ideal edge pixel. The FOM[23] metric measures how well the edges are preserved throughout the filtering process. This metric has a significant relationship with the overall quality score at 1% significance level.

5.7 Equivalent Number of Looks

Equivalent Numbers of Looks (ENL)[22] is a measure to estimate the speckle noise level in the image. The value of ENL depends on the size of the tested region; theoretically a larger region will produces a higher ENL value than a smaller region. The formula for the ENL is

$$ENL = \frac{NMV^2}{NSD^2} \quad (14)$$

5.8 Deflection Ratio (DR)

The formula for the deflection ratio calculation is;

$$DR = \frac{1}{R*C} \sum_{r,c} \frac{(f_d(r,c)-NMV)}{NSD} \quad (15)$$

After speckle reduction the deflection ratio[20] should be higher at pixels with stronger reflector points and lower elsewhere.

5.9 Correlation Coefficient (CC)

For digital images, correlation is a measure of the strength and direction of a linear relationship between two variable. A correlation of 1 indicates a perfect one-to-one linear relationship and -1 indicates a negative relationship. The square of the correlation coefficient[24] describes the variance between two variables in a linear fit. The Pearson’s correlation coefficient is defined as;

$$r = \frac{\sum_i (f_i - f_m)(\bar{f}_i - \bar{f}_m)}{\sqrt{\sum_i (f_i - f_m)^2}\sqrt{\sum_i (\bar{f}_i - \bar{f}_m)^2}} \quad (16)$$

where, f_i and $\bar{f}_i$ are intensity values of ith pixel in noisy and denoised image respectively. Also, f_m and $\bar{f}_m$ are mean intensity values of noisy and denoised image respectively.

5.10 Execution Time

Execution Time(ET) [25]of a denoising filter, is defined as the time taken by a processor to execute an algorithm when no other software, except the operating system (OS), runs on it. Execution time is referred with respect to the system's clock time-period. The execution time taken by a filtering algorithm should be low for real-time image processing applications. Hence, when all metrics give the identical values then a filter with lower execution time is better than a filter having higher execution time.

6. RESULTS AND DISCUSSION

The experiments were carried out on a Core i3; 2.4 GHz processor with 4GB RAM using MATLAB R2009. An objective evaluation of the existing denoising filters like Enhanced Lee filter, Weiner filter, Total Variation filter and Bilateral filter and proposed adaptive Lee filter is given in Table 1. The proposed adaptive Lee filter has produced a higher PSNR value compared with other existing filters equally it has produced a higher RMSE value than other existing filters. But for agood denoising filter the PSNR value should be high with the RMSE value close to zero.

The higher IQI value of the proposed adaptive Lee filter indicates that quality of the denoised image is very close to 1, indicating that the level of distortion to the denoised image is very less. The SSIM value is high for total variation filter, indicating that the structural similarity of the denoised image is close to the structures of the original image even after removing the noise.

The NMV value and NSD value are very high in the proposed adaptive Lee filter whereas the existing filters have less value indicating that the content of speckle level is more in the denoised image. For the measure of ENL there is a slight difference between Bilateral filter and the proposed adaptive Lee filter indicating better speckle removal in an larger uniform area.

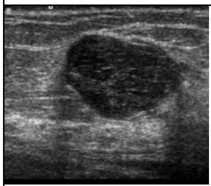
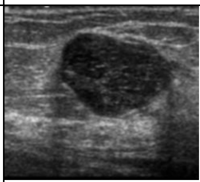
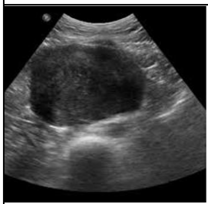
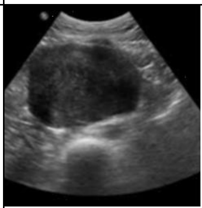
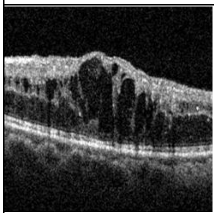
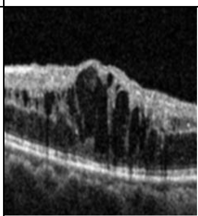
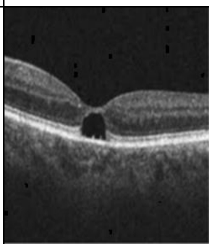
The higher DR value in the proposed adaptive Lee filter indicates strong reflecting pixels in denoised image. The FOM value indicates that the proposed adaptive Lee filter is able to provide better edge preservation than Bilateral filter. The higher CC value of the proposed adaptive Lee filter indicates that there is a better linear relationship between noisy image and denoised image.

Visual results of the proposed adaptive lee filter are listed in Table 2. Figure (a),(c),(e),(g) are two noisy ultrasound and two noisy optical coherence tomography images. Figure (b),(d),(f),(h) are denoised ultrasound and optical coherence tomography images obtained using the proposed method.

Table 1. Performance Evaluation of existing denoising filters with proposed adaptive lee filter.

mage Metrics	*xisting Spatial Domain Filters*				*roposed*
	Enhanced Lee	*Weiner*	*otal Variation*	*Bilateral*	
SNR	*6.04*	*6.13*	*8.78*	*0.20*	*1.1135*
MSE	*.01*	*.32*	*.98*	*1.52*	*9.133*
QI	*.8554*	*.9517*	*.9520*	*.9575*	*.9914*
SIM	*.7893*	*.8845*	*.9214*	*.9204*	*.8975*
MV	*3.72*	*9.45*	*7.92*	*6.62*	*8.2771*
SD	*.42*	*.92*	*.87*	*.01*	*.7910*
NL	*3.6621*	*9.291*	*5.2145*	*8.2367*	*8.6290*
R	*.0014*	*.0238*	*.0008*	*.03436*	*.6198*
OM	*A*	*A*	*A*	*.8263*	*.8125*
C	*.0209*	*.0762*	*A*	*A*	*.6550*

Table 2. Visual results of proposed adaptive lee filter.

oisy Image	enoised Image
 ig (a)	 ig (b)
 ig (c)	 ig (d)
 ig (e)	 ig (f)
 ig (g)	 ig (h)

7. CONCLUSION

As a prerequisite, Ultrasound images and Optical Coherence Tomography images should undergo denoising before being interpreted by the medical expert. The proposed work was tested with 25 Ultrasound images and 25 Optical Coherence Tomography images. The images were obtained from online database. The proposed algorithms were evaluated with several image metrics. The results shows that the proposed method performed better than the existing filters, but the visual results shows that some amount of speckle noise was still present in the denoised image. Hence future work can be proposed to denoise the speckle effects of coherence images through wavelet transforms which promises to reduce the speckle noise while maintaining the edge details of the original image.

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