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PERFORMANCE EVALUATION OF SPECKLE REDUCTION FILTERS FOR OPTICAL COHERENCE TOMOGRAPHY IMAGES

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ABSTRACT

Medical Images play a vital role in the diagnosis of various diseases. Hence high resolution and reduced noise becomes vital while representing these images. The Medical imaging modalities using Ultrasound produces images which are affected by speckle noises which are multiplicative in nature, caused due to interference of the backscattered image. One such modality used in ophthalmology is the Optical Coherence Tomography. Various filtering techniques have been proposed to reduce these speckle noises by pertaining the required image information. This paper aims at evaluating various such proposed filters. OCT image acquired using Karl Zeiss was used for this purpose of evaluation. Various filters were tested for speckle affected OCT image and the performances of these filters were evaluated in terms of Mean Square Error, Signal to Noise Ratio, Peak Signal to Noise Ratio, and visual inspection. The system was designed using MATLAB, Intel core 2 duo processor and was tested with images obtained from a medical research center. Results show that homomorphic wiener filters show a better performance followed by Gaussian filters. The results of the tested system for OCT Images can also be generalized for any other ultrasound based modality images.

KEYWORDS: ***Interference, Speckles, Image Smoothing, Mean Square Error, Signal to noise ratio***

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I. INTRODUCTION

Medical Images are more prone to noise in the stage of acquisition. It is essential to remove these noises by pertaining all the required informations, so that the image quality and informations are least affected. Optical Coherence Tomography is one of the widely used procedures, which serves as a vital tool of diagnosis in the field of ophthalmology, except for a disadvantage that these images are corrupted by speckle noises. OCT cross sectionally measures the optical reflections from the internal structures of the biological tissues[1]. For a reliable diagnosis of various retinal disorders, it is essential to obtain a high resolution Image. The measurements of Intra Ocular Pressure do not necessarily predict the progression of various diseases like glaucoma[2]. Loss of vision and Optic Nerve Head cupping are being detected only after 50% vision loss[3]. It is also necessary to properly image the retinal nerve fiber layer (RNFL) which is comparatively a layer of higher scattering than any other retinal structures. The backscattered light from RNFL strongly depends upon the incident angle of light[4,5]. These reflecting and backscattering rays raises some practical limitations on OCT. Independent of the texture of the surface, these backscattered and reflected light waves tend to interfere, thereby causing dark and bright spots. These noises are referred to as speckle noises, which are multiplicative in nature. This speckle formation is influenced by various parameters of the light source and detectors. Speckles are commonly formed due to multiple backscattering of beam and random delays in forward propagating and returning beams. When a large number of polarized quasi monochromatic waves with random phase combine, a fully developed speckle pattern is formed. Note that if all the backscattered are made to constructively interfere, it could be seen that the noise would disappear and contrast would be greatly enhanced. Speckles could be classified generally as signal carrying and signal degrading speckles, based on their origin. Speckles caused due to single backscattering are generally more informative and signal carrying in nature. It is necessary to preserve these informations howmuch ever possible while preprocessing the images. These types of speckles could also be differentiated by the spot sizes of correlation. Various filters used in speckle noise reduction are evaluated in terms of mean square error, signal to noise ratio, as well as improvisation in visual quality. The research work explains various filters used in reduction of speckle noises and the experimental analysis of these filters and their performance.

II. SPECKLE NOISE REDUCTION

Various methodologies proposed for reduction of speckle noises include, median filters[6-8],homomorphic wiener filter[9], multiresolution wavelet analysis[10], adaptive smoothing[11], frost filter[12-14], diffusion filter[15-19]. It could be understood that the appropriate method of reducing the speckle noises is the one which enhances the image by preserving the edges and lines in the image[7,20,21].

Mean Filters

Mean filters are simple smoothing filters which reduces the amount of variation in intensity between the neighbor pixels of the image. A window of standard sizes is generated and spatial filtering is performed using this window on the image. This filter computes the sum of all pixels in the slided filter window and then divides the sum by the number of pixels in the filter window[22-24]. The algorithm is so simple. The window is placed over the image. Average is taken (Sum up the elements and divide the sum by the number of elements).

New pixel value = Sum (W*image pixel value)/ Number of pixels (2.1)

where W is the weight factor, which is the ratio of standard deviation and mean. It could be understood that when a mean filter is used, a single pixel with a very unrepresentative value can significantly affect the mean value of all the pixels in its neighborhood. The major disadvantage is that when the filter neighborhood straddles an edge, the filter will interpolate new values for pixels on the edge and so will blur that edge. This may be a problem if sharp edges are required in the output.

Frost Filters

Designing of frost filters are dependent on factors that Speckle noise is a multiplicative noise, i.e. it is in direct proportion to the local grey level in any area. Also the signal and the noise are statistically not dependent on one another. It is exponentially weighted averaging filter which is dependent on the variation coefficient. The coefficient of variation is given by the ratio of local standard deviation to the local mean of the noise corrupted image. These are weighted filters whose weight factors decrease with distance from the pixel of interest.

New pixel value = Sum ($W*e^{-Wt}$) (2.2)

Adaptive smoothing filters

These are conventional filters of smoothing except that smoothing is done pixel wise iteratively, based on the input image and intensity of the noise. The filter coefficients adapts to the local changes in image statistics for n iterations specified by the user. For multiplicative noise, the adaptive noise smoothing filter is a systematic derivation of Lee's algorithm with some extensions that allow different estimators for the local image variance[25]. The filter entirely depends on the image statistics and no other priori informations on the original image are required.

Gaussian Filters

It is similar to any other smoothing filter except that the extent of smoothing/ noise removal is dependent on the standard deviation of the Gaussian. It is a mean filter which uses a different kernel that gives the shape of a Gaussian (`bell-shaped') hump. It could be understood that the weights of the spatial filters varies based on the standard deviation. The surrounding pixels with lesser deviation and closer as neighbour is given with a higher weightage, whereas, pixels with higher deviation and distant from the center pixel is given with a lesser weightage

Bilateral Filters

A bilateral filter is a non-linear filter which could be understood as an advancement of Gaussian filter in which the weighting of the filter coefficients is with the corresponding relative pixel intensities. It aims at smoothing the image by preserving the edges. Each pixel is replaced by weighted average of intensity values of the neighbourhood pixels. Pixels that are very different in intensity from the central pixel are weighted less even if they are close neighbours to the central pixels. This weight can be based on a Gaussian distribution. The weights depend on the euclidean distance of pixels, and the radiometric differences. Various artifacts included in image due to bilateral filtering include Staircase effect and Gradient reversal (introduction of false edges).

New pixel value = Avg (W*Image pixel value)(2.3)

where, W is the weight which is varied for every surrounding pixels

Anisotropic Diffusion Filters

Diffusion could be understood as balancing the changes in concentration of an image.Anisotropic diffusion is a generalization of this diffusion process, which 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. The rate to which the image should be diffused is dependent on the divergence of the surrounding pixels with respect to the center pixel. These filters are more commonly used in segmentation and edge detection, as they are comparatively good in preserving the edges even while smoothing the other regions of the image.

Homomorphic Wiener and Wavelet Filters

Homomorphic filters are commonly used in removing multiplicative noises. It normalizes the brightness throughout the image and enhances the contrast. Not restricting to preprocessing, these filters can also be used in enhancing the image. Illumination and reflectance components of an image are separated and then wiener and wavelet filters are applied to these components separately, after which it is recombined. The multiplicative noises are made additive by taking logarithm. These noises which are made additive are then removed linearly using wavelet and wiener filters. The basic idea is to convert the multiplicative noise into additive component and the remove them.

III. EXPERIMENTAL ANALYSIS AND DISCUSSION

Various filters as explained in section 2 were designed and evaluated for a speckle noise affected Optical Coherence Tomography image. Fig. 1 shows an OCT image with speckle noises and its monochrome image. The performances of the filters are evaluated in terms of the mean squared error (MSE), Signal to noise Ratio (SNR) and Peak Signal to Noise Ratio (PSNR).

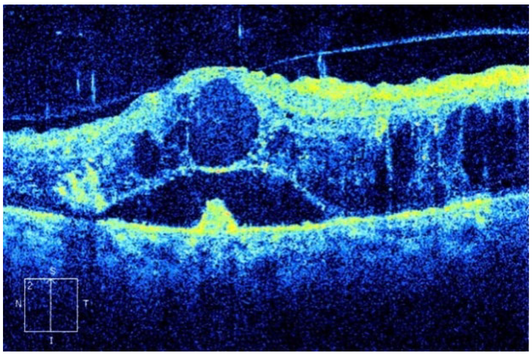

Figure 1
Speckle noise affected OCT Image.

Mean Squared Error is the average value of the squared values of the error between the original image and the estimated image. Signal to noise ratio gives the ratio of the concentration of the signal/ required data with that of the noise. Peak Signal to Noise ratio gives the ratio of peak power of the signal with that of the noise. These parameters are expressed in equations 3.1, 3.2, 3.3.

MSE = Mean(error^2) ***(3.1)***
SNR = Signal power/Noise power ***(3.2)***
PSNR = Peak Signal power/Peak Noise power ***(3.3)***

For an image to be with more desirable qualities, the SNR and PSNR are expected to be greater, which means that the intensity of noise must be much lesser. The outputs of various filters with various parameters are shown in fig. 2 and fig. 3.

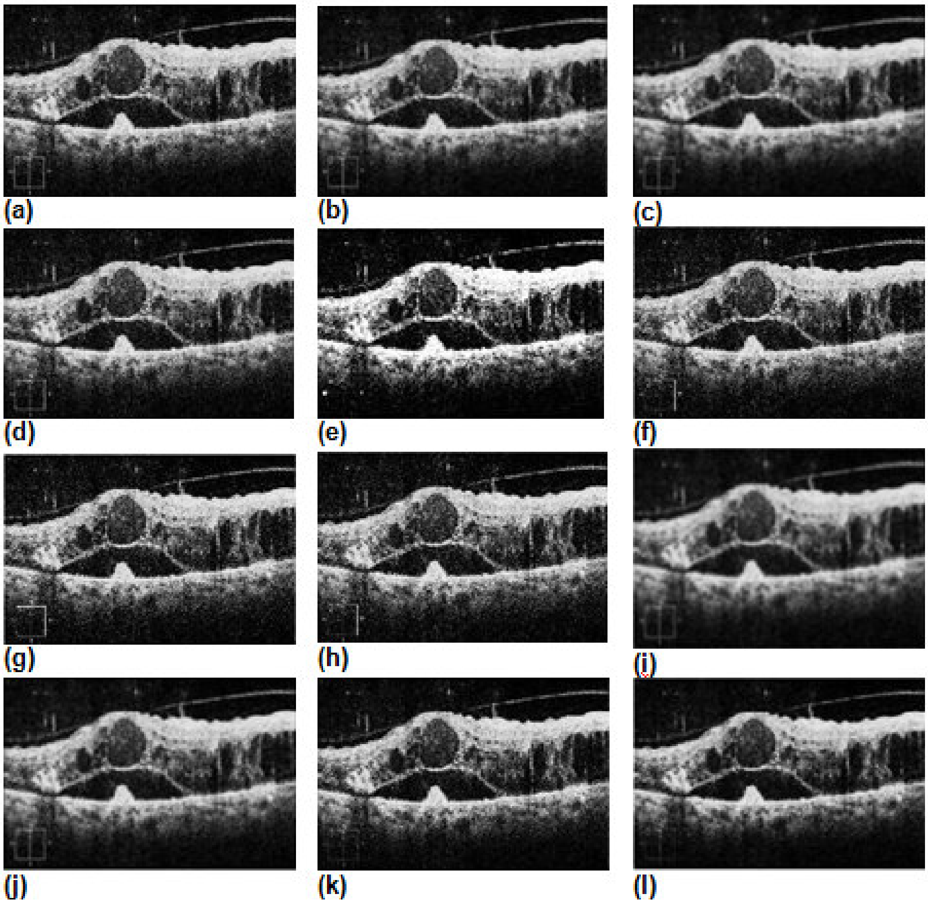

Figure 2

Output of various speckle reduction filters. (a) Mean filter 3*3, (b) Mean filter 5*5, (c) Mean filter 7*7, (d) Frost filter, (e) Adaptive smoothing filters, (f) Gaussian Filters 3*3, (g) Gaussian Filters 5*5, (h) Gaussian Filters 7*7, (i) Bilateral filters, (j) Anisotropic diffusion filters, (k) Homomorphic Wiener filters 3*3, (l) Homomorphic Wiener filters 5*5.

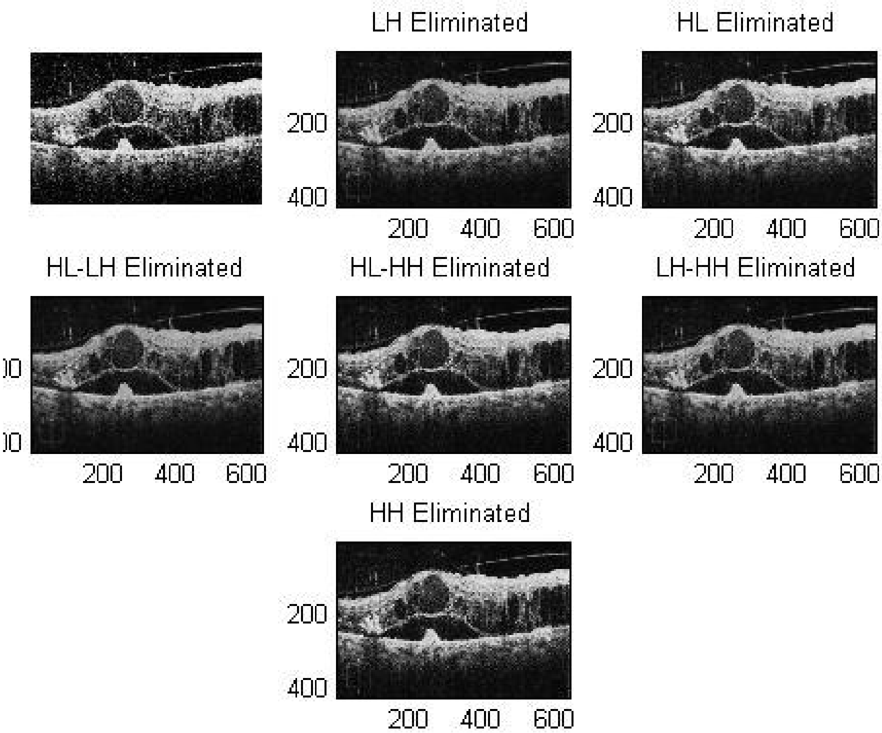

Figure 3
Output of various band eliminated homomorphic wavelet (db2) filters

Filter	MSE	SNR	PSNR
Mean (3*3)	0.0035	72.2718	72.6871
Mean (5*5)	0.0078	68.7923	69.2076
Mean (7*7)	0.0103	67.5839	67.9992
Adaptive smoothing	0.0106	66.9773	67.8866
Anisotropic Diffusion	0.0076	68.8824	69.2977
Frost	0.0028	73.2101	73.6254
Gaussian (3*3)	0.00005	81.048	81.4633
Gaussian (5*5)	0.00005	81.0183	81.4337
Gaussian (7*7)	0.00005	81.0183	81.4337
Homomorphic wiener	$1.2*10^{-7}$	97	97
Homomorphic wavelet - LH	2.1599	44.3712	44.7865
Homomorphic wavelet - HL	2.1613	44.3684	44.7837
Homomorphic wavelet - HL – LH	2.1723	44.3463	44.7616
Homomorphic wavelet - HL – HH	2.1433	44.4046	44.8199
Homomorphic wavelet - LH – HH	2.1557	44.3796	44.7949
Homomorphic wavelet - HH	2.1544	44.3822	44.7975

Table 1
Performance metrics of filters in speckle noise reduction

The SNR and PSNR parameters of the various filters used are represented in the fig. 4 and fig. 5.

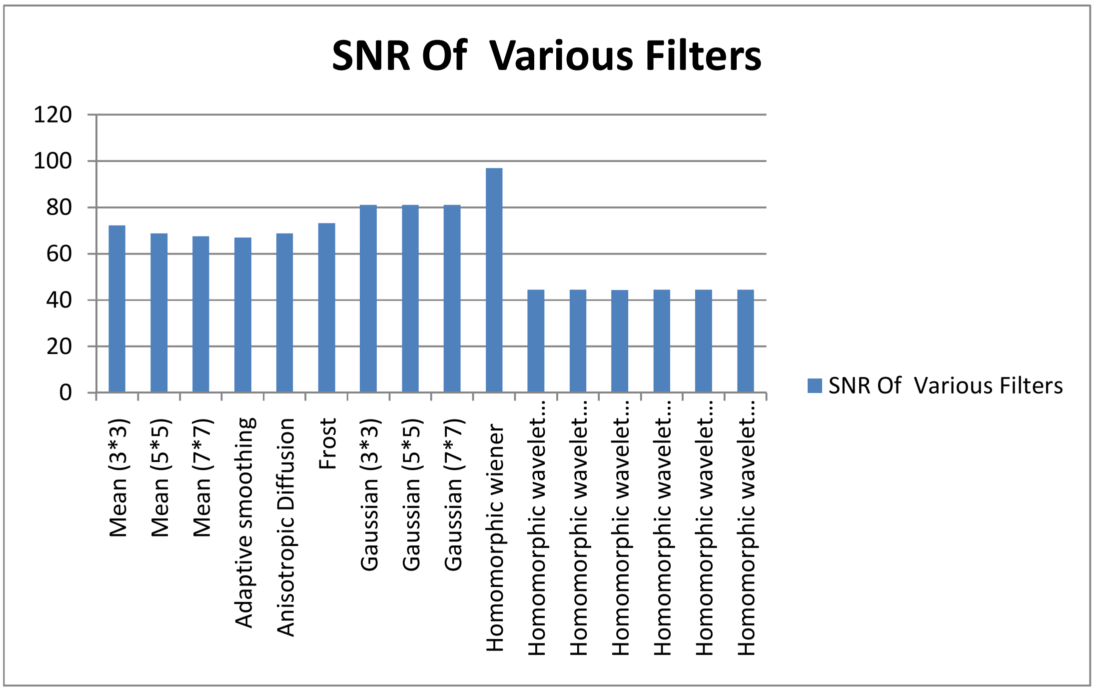

Figure 4
SNR Values of various filters

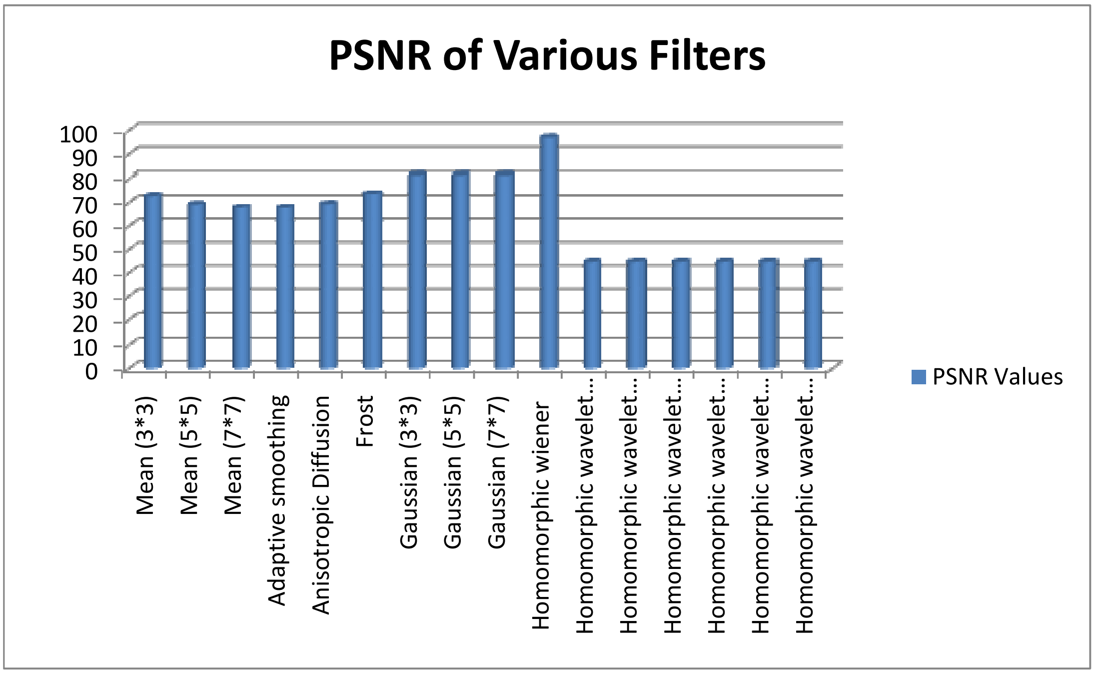

Figure 5
PSNR Values of various filters

From the results obtained, it could be seen that homomorphic filters are more effective in removing the speckle noises for the OCT images. The homomorphic wiener filter seems to show a better performance not only in analysis of the statistical parameters but also from the visual inspection.

IV. CONCLUSION

It could be seen that among the various filters evaluated, both statistically as well as visually. Most of the filters fail to remove the speckle noises in medical image, since the details about noise variance may not be identified. Most of the filters just average the data instead of removing the speckles. The computational results show that Homomorphic wiener filter is comparatively better, the reason being that the multiplicative noises are made additive and hence noise removal is much effective comparatively. Gaussian filter and frost filters also shows appreciable results following the homomorphic wiener filter. It could also be seen that irrespective of the size of the kernel, mean filter showed a poor performance. This is justifiable as the mean filters do not take more statistical properties into consideration. Also it could be seen that Homomorphic wavelet filters show poor performance than any other filters. The results are evaluated with OCT images, but are applicable for any imaging modality with speckle noises. The results are expected to be similar for other medical images including Ultrasound.

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