Identification of Noise in the Fundus Images

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Abstract— **Analysis of the tiny retinal vasculatures in retinal fundus images becomes difficult due to very low and varied contrast between the retinal vasculature and the background. Fundus fluorescein angiogram overcomes these problems and provides an excellent visualization of the retinal vasculature; however it is an invasive procedure requiring injection of contrasting agents. Further investigation of the RETICA method, a non-invasive method of image enhancement developed earlier, is reported in this paper. It was found that noise is present in the Retinex image. Thus, the identification of the noise in the Retinex image and its removal has been the focus of this research paper. The method used to identify noise is based on adaptive wiener filters (additive, multiplicative, and additive plus multiplicative filters) and the fundus model image and real fundus images are applied to these filters. It is observed that retinal fundus images contained both additive and multiplicative noise. The noise is reduced by using adaptive wiener filter (additive plus multiplicative adaptive wiener filter) based method which resulted in 2.84db an improvement in PSNR.**

Keywords—Retinex, Noise Models, Wiener Filter, PSNR

I. INTRODUCTION

Eye screening is vital in detection of diabetic retinopathy. There are five stages in diabetic retinopathy (DR) ranging from normal (No-DR), mild DR, moderate DR, severe non proliferative DR (NPDR) to PDR. The PDR stage is where there is a total loss of vision [1]. Haemorrhages, exudates and changes in the veins are some of the pathologies that, when present, characterise these DR classifications [2]. It was reported in a research carried out recently on the analysis of images of the fundus that as the severity level of DR advances, the fovea avascular zone size increases. The FAZ is observable in colour fundus images and in fundus fluorescein angiograms (FFA) [3].

This is due to the loss of the retinal capillaries in the perifoveal capillary network in DR cases [4]. A clinical study has shown that the FAZ increases with the severity level of DR [5]. In an earlier work, digital enhancement techniques such as Retinex and independent component (ICA) were used in combination called RETICA, to overcome the low and varied contrast problems of colour fundus images [6].

Over the last twenty years, there have been quite a variety of algorithms for image denoising as reviewed in the literature [7]. These algorithms have generally shown good performance; however, almost all have been designed to reduce or remove specific kinds of noise [8]. For example, one may work on Gaussian white noise while another may focus on non-Gaussian, speckle or impulsive (salt-and-pepper) noise [9].

The problem of identifying the nature of noise has been discussed by several researchers [10-12]. Proposing a method that is suitable for identifying the kind of the noise present in an image is quite challenging [13]. When the nature of the degradation is not known, its identification in an image is a vital step in information interpretation systems that are based on visualisation. In most real life images, there is no prior knowledge of the nature of the noise present in the image; however, most of the algorithms for filtering (Lee, Wiener) reported in related literature consider the nature of the noise to be known. This makes it necessary to estimate the statistical parameters of the noise [14]. It is vital that the nature of the noise with respect to the source of the noise is first determined using an authenticated method of identification. Otherwise, the result of the identification process will not be optimal.

It is thus necessary to have methods for identifying the noise present in an image so that the image can be denoised using an appropriate algorithm. Three basic noise models are available namely: multiplicative, additive, and additive plus multiplicative. Multiplicative or speckle noise as it is known, depends on the image while the additive noise is systematic by nature and is modeled quite easily, which means reducing or removing additive noise is not difficult. A model of the additive and multiplicative noise contained both additive and multiplicative noise. The additive and multiplicative noise occurred due to imaging methods and image modalities.

II. PROPOSED APPROACH

The Retinex algorithm [15] is used for contrast normalisation while the ICA algorithm [16] is used for contrast enhancement in a previously developed technique RETICA [6]. After contrast normalisation, the Retinex image is observed to contain noise. Before any denoising of the Retinex image, it is a very important to identify the noise type. There are two possible sources of the noise in fundus image. First, the noise could be due to image acquisition modality (in this the fundus camera) and the second possible source is the Retinex algorithm itself.

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The method to identify the type of noise in the fundus image (fundus model image or macula region of the green band and the Retinex image) is based on three steps. First, design the suitable filters based on noise models (Figure 1); second, apply filtering techniques on model fundus image, original macular region image and Retinex image and determine the PSNR of each stage (Figure 2). PSNR is calculated according to Equation 1.

$$\mathrm{PSNR} = 20\log_{10}\left(\frac{255}{\sigma}\right) \qquad (1)$$

In Equation 1, σ is the standard deviation of the image and 255 is considered as peak value of image.

Design of Adaptive Wiener Filters: In this step, adaptive wiener filters are used. The first adaptive wiener filter is basically designed to remove the additive noise. A second adaptive wiener filter is designed as a multiplicative filter to remove multiplicative noise and a third adaptive wiener filter is designed as an additive and multiplicative wiener filter to deal with both multiplicative and additive noise. In Figure 1, three adaptive wiener filters (additive, multiplicative, and additive plus multiplicative filters) are designed according to assumptions below:

Assumption 1: Noise is additive and uncorrelated with signal as shown in Equation 2

$$I'(x, y) = I(x, y) + n(x, y) \qquad (2)$$

Assumption 2: Noise is multiplicative and correlated with signal as shown Equation 3.

$$I'(x, y) = I(x, y) * n(x, y) \qquad (3)$$

Assumption 3: Noise is both additive and multiplicative as shown in Equation 4.

$$I'(x, y) = I(x, y) * n(x, y) + n(x, y) \qquad (4)$$

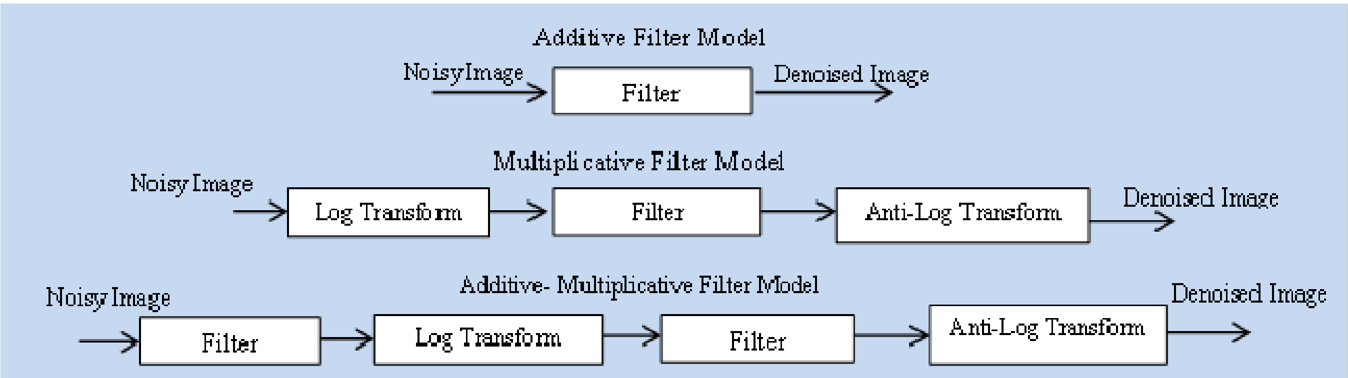


Figure 1. Modeling of Adaptive Wiener Filter

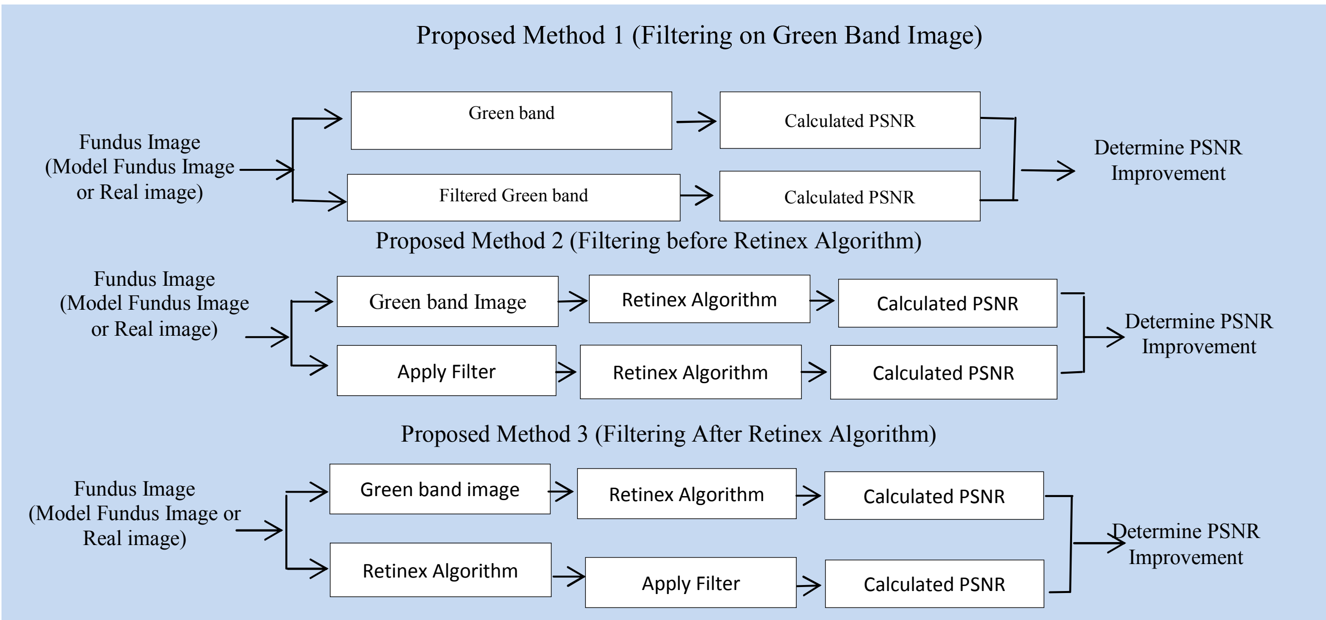


Figure 2. Proposed Methods for identification of Noise in Retinal Fundus Image

Proposed Methods for identification of Noise in Retinal Fundus Image:

The above adaptive wiener filters (additive, multiplicative, and additive plus multiplicative filters) are applied to the fundus model image and real fundus images. For the real fundus images, the filters are applied on the green band image and the Retinex image i.e., before and after processing through the Retinex process to identify the nature of noise. The PSNR improvement is observed before and after the Retinex process.

Referring to Figure 2, an adaptive wiener filter is applied on green band of fundus model image and real fundus image in Method 1. The PSNR improvement of each filter is determined. The filter which resulted in the highest PSNR improvement indicates the type of noise in the image. In Methods 2 and 3, the filters are applied before and after the Retinex algorithm and PSNR at each stage has been calculated. The PSNR of unfiltered Retinex image has also been determined. Similarly, the PSNR improvement is observed between PSNR of unfiltered Retinex image and PSNR of filtered Retinex image to determine the nature of noise.

III. RESULTS AND ANALYSIS

Results of Method 1:

Figure 3 shows the PSNR values for green band fundus model image and after filtering by the three wiener filters.

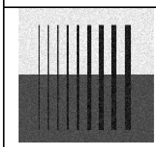
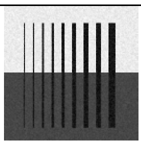
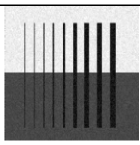
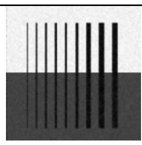
Green Band Image	An Additive Wiener Filtered Green Band Image	A Multiplicative Wiener Filtered Green Band Image	An Additive-Multiplicative Wiener Filter Green Band Image
			
PSNR: 24.69db	PSNR: 24.89db	PSNR:25.01db	PSNR:26.98db

Figure 3. Results of Method 1 of Model Fundus Image

According to PSNR improvement, the additive and multiplicative wiener filter gave the best PSNR improvement of 2.29db. This indicates that fundus model image has additive and multiplicative noise. Similarly, the macula region of colour fundus image is processed through the adaptive wiener filters and PSNR values are shown in Figure 4. The highest PSNR improvement (1.1dB) is achieved with the additive and multiplicative wiener filter**.** Thus, the macular region of green band image contains both additive and multiplicative noise.

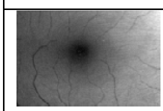
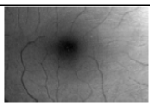
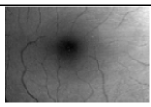
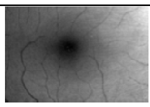
Green Band Image	An Additive Wiener Filtered Green Band Image	A Multiplicative Wiener Filtered Green Band Image	An Additive-Multiplicative Wiener Filter Green Band Image
			
PSNR:26.03db	PSNR:26.96db	PSNR:27.05db	PSNR:27.13db

Figure 4. Results of Proposed Method 1 on Green Band Fundus Image

The FINDeRs database has 175 images of which 50 images were No_DR, 40 Mild NPDR images, 30 Moderate NPDR images, 18 Severe NPDR images and 37 PDR images are used for validation of proposed Method 1. PSNR improvement between the additive and multiplicative wiener filtered macular green band image of FINDeRS database and the unfiltered green band image is observed. It is seen that PSNR improvement decreases slightly with increase in DR severity level. As shown in Figure 5 the average PSNR improvement at No_DR was 0.22db; at Mild NPDR 0.21db; at Moderate NPDR 0.2db; at Severe NPDR 0.19db and at PDR 0.18db.

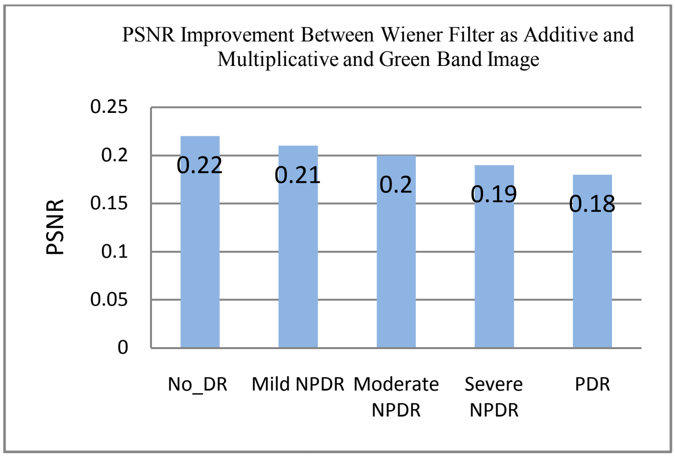


Figure 5. PSNR Improvement of Method 1 on FINDeRS Database

Results of Method 2:

In Method 2, the 3 adaptive wiener filters are applied before Retinex algorithm. The PSNR improvement between filtered Retinex algorithm (filtering is applied before Retinex algorithm) and unfiltered Retinex image is observed. The results are tabulated in Figure 6.

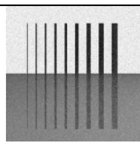
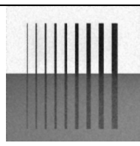
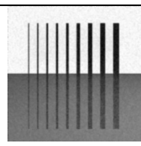
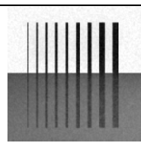
Retinex Image (Without Filtering)	An Additive Wiener Filtered Retinex Image	A Multiplicative Wiener Filter Retinex Image	An Additive-Multiplicative Wiener Filter Retinex Image
			
PSNR: 26.68db	PSNR:27.01db	PSNR:27.58db	PSNR:27.93

Figure 6.Results of Method 2 on Model Fundus Image

Again, the additive and multiplicative wiener filtered gave the highest PSNR improvement (1.92db), which indicates that fundus model image processed according to proposed Method 2 contained both additive and multiplicative noise. Similarly, Method 2 is applied on the macula region of real fundus images as shown in Figure 7.

It is clearly seen that the additive and multiplicative wiener filter gave highest PSNR improvement of 2.35db, which indicates that Retinex fundus image analysed according to Method 2 contained both additive and multiplicative noise.

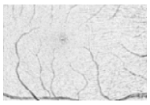
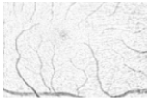
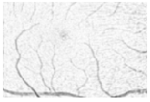
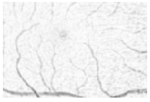
Retinex Image (Without Filtering)	An Additive Wiener Filtered Retinex Image	A Multiplicative Wiener Filter Retinex Image	An Additive-Multiplicative Wiener Filter Retinex Image
			
PSNR: 39.56db	PSNR:40.57	PSNR:41.03	PSNR:41.91

Figure 7.Results of Method 2 on Retinex Fundus Image

FINDeRs database is used for validation of PSNR improvement between an additive and multiplicative wiener filtered macular region of Retinex image and unfiltered Retinex image was calculated. No_DR images gave average PSNR improvement of 4.03db, Mild NPDR was 3.99db, Moderate NPDR was 2.96db, Severe NPDR was 2.56db and PDR was 1.96db as shown in Figure 8**.**

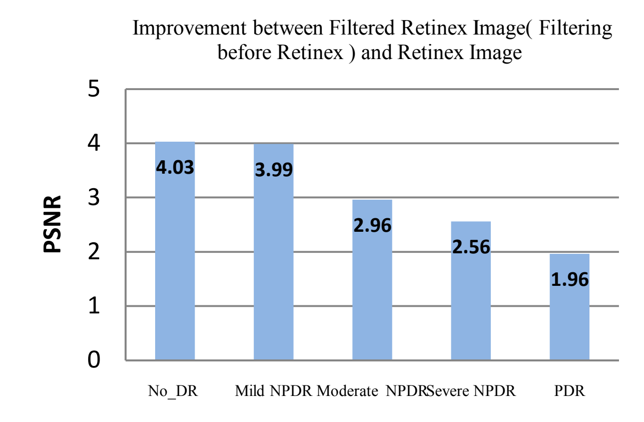


Figure 8. PSNR Improvement of Method 2 on FINDeRS Database

Results of Method 3:

In Method 3, the 3 adaptive wiener filters are applied after Retinex algorithm. PSNR of the filtered Retinex images and PSNR improvements between filtered Retinex image (filtering is applied after Retinex algorithm) and unfiltered Retinex image are determined as depicted in Figure 9.

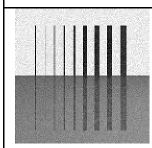
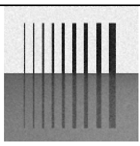
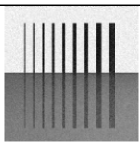
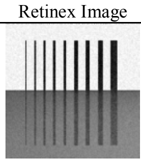
Retinex Image (Without Filtering)	An Additive Wiener Filtered Retinex Image	A Multiplicative Wiener Filter Retinex Image	An Additive-Multiplicative Wiener Filter Retinex Image
			
PSNR:26.68	PSNR:27.09	PSNR:27.82	PSNR:28.91

Figure 9 .Results of Method 3 on Model Fundus Image

It was found that the additive and multiplicative wiener filter gave highest PSNR improvement of 2.23db, which indicates that Retinex fundus model image contained both additive and multiplicative noise.

Similarly, Method 3 is applied on macula region of real fundus image as shown in Figure 10. The PSNR of the Green band fundus image processed through Retinex algorithm is found to be 39.56db. PSNR improvement between an additive wiener filtered Retinex images and unfiltered Retinex image is 1.49db. PSNR improvement between a multiplicative wiener filtered Retinex Image and unfiltered Retinex image is 2.25db.

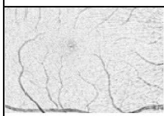
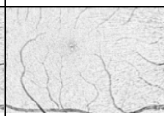
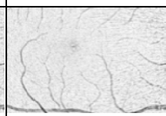
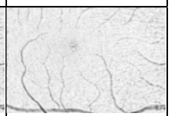
Retinex Image (Without Filtering)	An Additive Wiener Filtered Retinex Image	A Multiplicative Wiener Filter Retinex Image	An Additive-Multiplicative Wiener Filter Retinex Image
			
PSNR:39.56	PSNR:41.05	PSNR:41.93	PSNR:42.82

Figure10. Results of Method 3 on Retinex Image

PSNR improvement between an additive and multiplicative wiener filtered Retinex image and unfiltered Retinex image is 3.26db. The additive and multiplicative wiener filter gave highest the PSNR improvement of 3.26db**.** This indicates that Retinex fundus image contained both additive and multiplicative noise.

The PSNR improvement based on analysis of three proposed methods proves that green band fundus image or model fundus image and Retinex image contains additive and multiplicative noise. Figure 11 shows the PSNR values of FINDeRs database using Method 3.

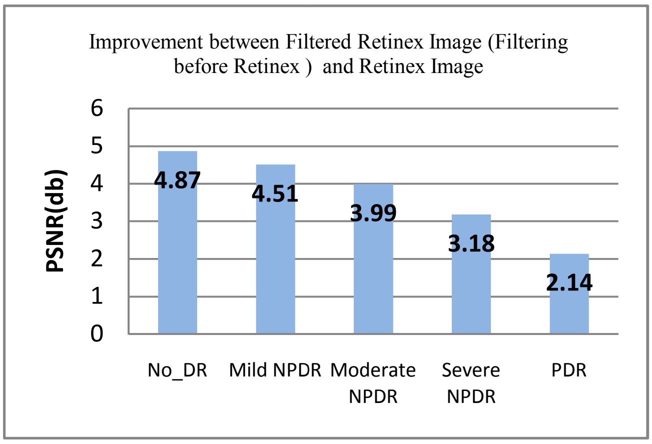


Figure 1. Shows the PSNR values of FINDeRs database using Method 3.

The noise occurring in retinal fundus image is due to two sources. Firstly, it is due to fundus camera and secondly the Retinex algorithm. Multiplicative noise occurred due to the flash of fundus camera and additive noise is due to camera electronics and ratio-product-reset-average operation of Retinex algorithm. It is also observed that filtering applied before Retinex algorithm did not give better PSNR improvement as compared to filtering applied after Retinex algorithm. This observation shows the significance of denoising technique required after Retinex algorithm. The comparison of PSNR improvement at each DR stage between an additive and multiplicative wiener filter applied before and after Retinex algorithm can be seen in Figure 12.

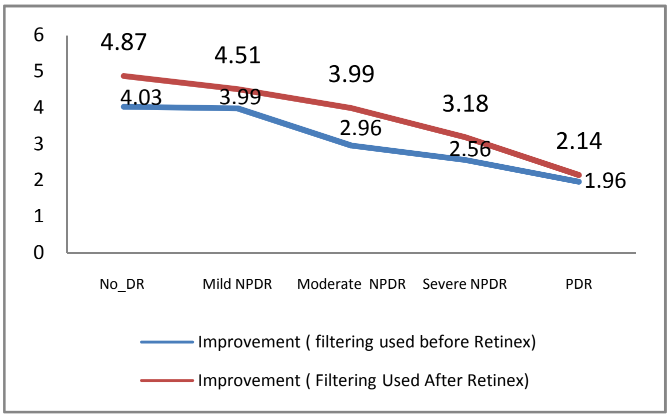


Figure12.PSNR Improvement Comparison

Referring Figure 12, at all stages, the highest PSNR improvement is achieved when an additive and multiplicative wiener filter applied after Retinex algorithm. The average PSNR improvement was 3.8db when an additive and multiplicative wiener filter applied after Retinex algorithm as compared to PSNR improvement was 2.84db when an additive and multiplicative wiener filter was applied before Retinex algorithm.

VI. CONCLUSIONS

This research work is based on the noise identification in Retinal Fundus image when undergoing a non-invasive technique of image enhancement called RETICA. RETICA contained two stages Retinex and ICA. It was found that the Retinex image is contained noise. The identification of the noise in the fundus image (model fundus image or real fundus image) has been the focus in this research work. The approach used to identify noise is based on 3 adaptive wiener filters (additive, multiplicative, and additive plus multiplicative filters) and determining the highest PSNR improvement among three adaptive wiener filters. It is observed that Retinal fundus image contained additive and multiplicative noise. This noise identification approach is one of the major contributions in the field of image processing because a digital image is acquired through imaging system or modalities.

It is also observed that filtering applied before Retinex algorithm did not give better PSNR improvement and it gave 1.96db as compared to PSNR improvement of 2.14db of filtering applied after Retinex because Retinex algorithm also gave noise due to its ratio-product-reset-average operation. Noise is occurred due to image modality (Fundus camera) and image method (Retinex Algorithm). According to analysis in terms of PSNR improvement, it is better to applied filtering after Retinex algorithm to achieve noise free image because filtering after Retinex algorithm handle noise occurred due to flash of fundus camera and noise occurred due to ratio-product-reset and average operation of Retinex algorithm else filtering applied before Retinex algorithm just handle the noise occurred due to flash of fundus camera. This observation shows the importance of denoising technique in image enhancement such as RETICA.

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