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# Observation Model for Retinal Image Normalization

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**Abstract--**Retinal images are often acquired to diagnose diseases like diabetes, hypertension, and glaucoma. In acquisition process images are non-uniformly illuminated and exhibit local luminosity and contrast drift. This may affect diagnostic process and results in deriving diagnostic parameters. We proposed method that estimates background of retinal images by sub sampling and interpolation. This method based on estimation of luminosity and contrast variability in the background part of image and the subsequent compensation of this variability in whole image. Experimental results show that this method can effectively achieve non uniform illumination and contrast normalization.

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## 1. Introduction

Retinal fundus images are important diagnostic basis to gather clinical information. It is very important for eye specialist to be able to clearly detect lessons present in the image. Retinal images are acquire with fundus camera that record illumination light reflected from the curved surface thus it makes certain lesion areas difficult to be observed and affects diagnosis process and its outcome. Thus the normalization is a necessary prerequisite for lesion detection.

The normalization methods of retinal images are mainly based on space and frequency domain more no of methods are introduce in frequency domain. Among then, to normalize image luminosity using high-passed filter, is used by Gonzalez and Woods in 2002 and Dhawan in 2003. M. Kuivalainen does normalization of images through the ratio of green and red channel of RGB Color images. R. J. Radke uses homomorphic filter that reduces low frequencies (Illumination) and increases high frequencies (Reflection). Y K Path uses the model that uses adaptive filtering mask that suppressed low frequency portion of the image as well as improve non uniform luminosity and contrast.

In space variant filtering shed correction method is used by T. Spencer. To enhance image appearance, locally adaptive contrast enhancement is used by Wallis. Wang in 2001 presents and approach that extracts the vessels pixels estimation of illumination drift in pixels and its subtraction from observed image. Sathit Intajag used fuzzy set to enhance the images by partitioning the image histogram into multi modes.

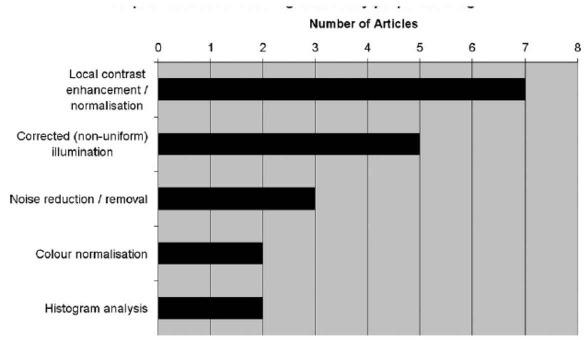


**Fig. 2.** Figure shows the frequency of distribution of different preprocessing techniques.

A new method is required as retinal images contain many features like optic disk or various lesions that should be more visible by normalization process. Locally adaptive non linear filters decrease global difference between bright and dark pixels, even if it produces better local contrast. The method by Wang uses vessels as descriptors. But, due to luminosity variation it is not that efficient. Here we propose a new method based on model of observed image for normalizing for both luminosity and contrast. Luminosity and Contrast drifts are observed from background part of the image and are used for normalization of whole image. Normalization is performed for both within and between images even if this method is used for retinal images, this can be used to any non-uniformly illuminated image.

## 2. Material and methodology

The retinal images (digital Fundus angiography) used, are from publically available database (DRIVE). The images were of 565 X 584 .tif images with $35^{O}$ FOV. The algorithms are tested on these 20 available images.

2.1 The observed model

The original retinal fundus images can be regarded as the combination of ideal background image and foreground image.

$$I = F(I^O) = F(I^O_b + I^O_f) \quad (1)$$

Where, $I^O$ is original image & $I^O_b$ is original background image & $I^O_f$ is original foreground image. F (.) represents acquisitions transformation function. $I^O_b$ is free of vascular structure where as vascular structures as modeled as $I^O_f$.

$$I(x, y) = C(x, y) * I^O(x,y) + L(x,y) \quad (2)$$

$$I^O(x,y) = I^O_b(x,y) + I^O_f(x,y) \quad (3)$$

According to (2) we get:

$$I^O(x,y) = \frac{I(x,y) - L(x,y)}{C(x,y)} \quad (4)$$

The recovery of estimation $\hat{I}^o$ of original image $I^O$ is based on estimation of C and L and the compensation of observed image *I* as:

$$\hat{I}^o(x,y) = \frac{I(x,y) - \hat{L}(x,y)}{\hat{C}(x,y)} \quad (5)$$

It is rather difficult to express properties of $I^O_f$ .On the other hand $I^O_b$ can be statistically modeled as normal distribution:

$$I^O(x,y) \sim N(\mu_b, \sigma_b) , \quad (6)$$

μb is mean value and σb is standard deviation representing natural variability of retinal fundus pigment.

Using above model of $I^O_b$ and it's further simplification ,the background pixel can be statistically given as:

$$I(x,y) \sim \mathcal{N}(L(x,y), C(x,y)), \quad (x,y) \in \mathcal{B}. \quad (7)$$

2.2 Boundary Singularity Processing

Due to the peripheral of retinal fundus image has lower luminosity, which results in many pixels departed from the retinal background and inducing large normalized negative value during the process by (5).We call this kind of pixels as singularity points.

The extraction of background set β requires following assumptions, for any pixel of image in a neighborhood N of appropriate size S:

1) Both L and C are constant.
2) Minimum 50% pixels are background pixels.
3) All background pixels should have different pixel value than foreground pixel.

The first assumption is based on model, that states content of L and C are concentrated in the low frequencies, whereas second on indicates that sufficient background area must be present in each N. Third tells that pixels belong to background or not can be determine simply by examining their intensity.

Firstly, for each pixel (x, y) in the image, mean, $\mu_N$ (x, y) and standard deviation $\sigma_N$ (x, y) of intensities in N are estimated. Estimator $\hat{\mu}_N$ for $\mu_N$ (x, y) is used as sample mean and $\hat{\sigma}_N$ estimator is used as sample standard deviation. Pixel (x, y) is said to be background pixel if its intensity is closed to mean intensity. The background set β can be achieved according to Mahalanobis distance from $\hat{\mu}_N$, $d_M$ of pixel (x, y) from $\hat{\mu}_N$.

$$d_M = \left| \frac{I(x,y) - \hat{\mu}_N}{\hat{\sigma}_N} \right| \quad (8)$$

If $d_M$ is lower than threshold, then (x, y) belongs to background. In order to reduce computational burden sub-sampling and interpolation techniques had been adopted. Experiment images use a values of t = 1 and s = 50 for 565 X 584 fundus images has been chosen. An example of estimated background image is shown in fig2(a).Estimated L(x,y) and C(x,y) is shown in fig 2(b) , (c) respectively.

2.3 Estimation of luminosity and contrast drifts

Given the background set β, L(x,y) and C(x,y)can be derived for each pixel.From (6) and under the first assumption background pixel intensities in each N are independent ,identically distributed random variables. L(x,y) and C(x,y) could be derived for each pixel by estimating mean value and standard deviation of this distribution in *N*.

This approach requires more computational efforts, and also we are dealing with sparse set of pixels which make filtering more difficult. Thus, a square processing, that divides image into tessellation of squares $S_i$ is used. From the background set β in $S_i$, mean and standard deviation is estimated by respective estimator. Full luminosity and contrast drift were then obtained by applying bi-cubic interpolation on the sub-sampled images.

By pint transformation to each pixel the normalized image of observed image $I^O$ is obtained.

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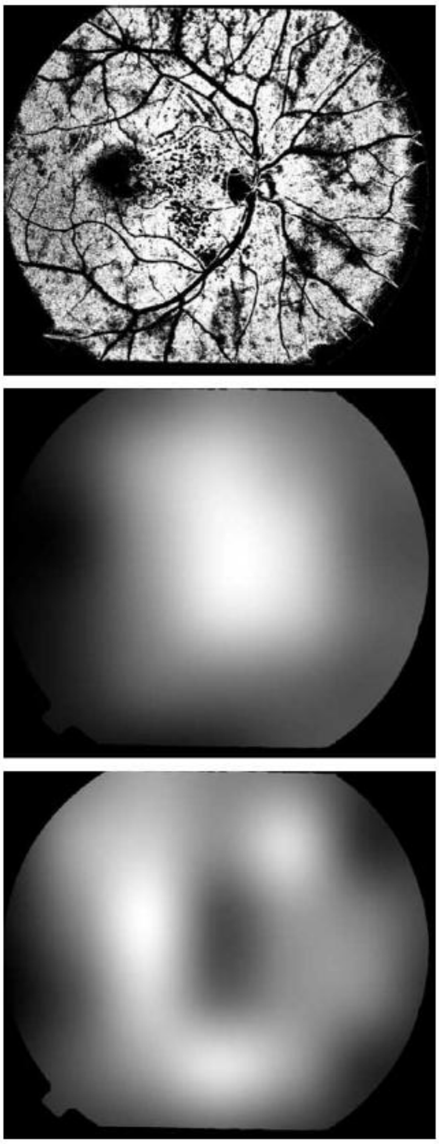

Fig. 2. Computed images: estimated background image (top, white pixels); estimated illumination drift $\hat{L}$ (middle); estimated contrast drift $\hat{C}$ (bottom).

Computed images estimated background image (top, white pixels); estimated illumination drift L (middle); estimated constrast drift C (Bottom)

2.4 Color image normalization

Normalization of RGB color images can be performed y independently normalizing each color channel with the above procedure:

$$\begin{pmatrix} \hat{R}^o(x,y) \\ \hat{G}^o(x,y) \\ \hat{B}^o(x,y) \end{pmatrix} = \begin{pmatrix} \frac{1}{\hat{C}_R(x,y)} & 0 & 0 \\ 0 & \frac{1}{\hat{C}_G(x,y)} & 0 \\ 0 & 0 & \frac{1}{\hat{C}_B(x,y)} \end{pmatrix} \times \left[ \begin{pmatrix} R(x,y) \\ G(x,y) \\ B(x,y) \end{pmatrix} - \begin{pmatrix} \hat{L}_R(x,y) \\ \hat{L}_G(x,y) \\ \hat{L}_B(x,y) \end{pmatrix} \right]. \tag{8}$$

Independent normalization of color component does not maintain chromatic information. A recovery of chromatic distribution can be achieved by identifying image chromatic statistical distribution in the observed image,given by vectors of sample mean [$\mu_r$, $\mu_g$, $\mu_b$] and sapmle standard deviation [$\sigma_r$, $\sigma_g$, $\sigma_b$] ,and by applying it to normalized image:

$$\begin{pmatrix} \hat{R}_c^o(x,y) \\ \hat{G}_c^o(x,y) \\ \hat{B}_c^o(x,y) \end{pmatrix} = \begin{pmatrix} \sigma_R & 0 & 0 \\ 0 & \sigma_G & 0 \\ 0 & 0 & \sigma_B \end{pmatrix} \begin{pmatrix} \hat{R}^o(x,y) \\ \hat{G}^o(x,y) \\ \hat{B}^o(x,y) \end{pmatrix} + \begin{pmatrix} \mu_R \\ \mu_G \\ \mu_B \end{pmatrix}, \tag{9}$$

Where $[\hat{R}_c^o\ \hat{G}_c^o\ \hat{B}_c^o]$ represents the vector of image components normalized with respect to luminosity, contrast and chromatic information.

Conclusion:

The method proposed achieves non -uniformly luminosity and contrast normalization of retinal fundus images.On the other hand, it enhances the contrast of lesion areas without changing the characteristic of original physiological structure.

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