ILLUMINATION CORRECTION AND CONTRAST EQUALIZATION IN COLOUR FUNDUS IMAGES

Radim Kolar, Jan Odstrcilik, Jiri Jan, Vratislav Harabis

Brno University of Technology,
Faculty of Electrical Engineering and Communication,
Department of Biomedical Engineering,
Kolejni 4, 61200, Brno, Czech Republic
phone: + (420) 541 449 558, fax: + (420) 541149542, email: kolarr@feec.vutbr.cz
web: http://www.dbme.feec.vutbr.cz/

ABSTRACT

A method for correction of non-uniform illumination in colour fundus images based on the B-spline approximation of the illumination surface is presented. The control points for B-splines are determined from an original image, separately from the red, green and blue channel. The estimated illumination surface is used in a multiplicative model for fast correction. The proposed approach has been subjectively tested on new publicly available retinal image database DRIIL (Digital Retinal Images for ILumination correction), which contains 165 images. Objective testing has been conducted by investigating the influence of the proposed method on blood-vessel segmentation using another high resolution fundus image dataset of healthy and diabetic patients.

1. INTRODUCTION

The imaging of retina using advanced fundus cameras has became a standard imaging modality in many ophthalmologic clinics. The digital retinal images can be used for computer aided diagnosis of e.g. glaucoma, age-related macular degeneration, diabetic retinopathy etc. [1]. The diagnostic value of these images is based, of course, on the *image quality*. This means mainly image resolution (determined by camera resolution and field of view), contrast of objects on retina (blood-vessels, optic disc, nerve fibers, hemorrhages etc.) and uniformity of retina illumination. The enhancement of the last two quantities is considered in this paper.

Improper scene illumination due to non-ideal acquisition conditions can introduce severe distortions into the resulting image (see two examples of dark, low-contrast and non-uniformly illuminated retinal images in Fig.1 and Fig.2). These distortions are usually perceived as smooth intensity variations across the image and must be eliminated. According to the terminology commonly used in processing of magnetic resonance images we call these systematic intensity level inhomogeneities as the *bias field*. Most existing bias correction methods assume that the bias field is multiplicative, slowly varying, and tissue independent. These assumption are used also in our work.

The known illumination correction methods can be categorized as filtering based, segmentation based, surface fitting based and other methods. Specific methods for illumination correction were proposed for retinal image processing and analysis. Simple and fast method using large-kernel median filter to obtain a low-pass correction coefficients were used for confocal scanning laser ophthalmologic image preprocessing in [2]. Authors of [3] model the bias field of a fundus image as a white Gaussian random field and use Mahalanobis distance for background pixel classification. Multiplicative acquisition model is used also in many ophthalmologic applications as a basic preprocessing step. Contrast normalization using high-pass filtered image is used in [4] as one step of microaneurysm detection procedure. Additive model of non-uniform illumination is used in [5] together with adaptive histogram equalization. A simple and efficient procedure for bias field correction is also applied before registration of fundus and optical coherent tomographic images [6]. The method proposed here, is based on a combination of surface approximation approach and filtering approach to obtain a reliable estimate of the bias field in colour fundus images.

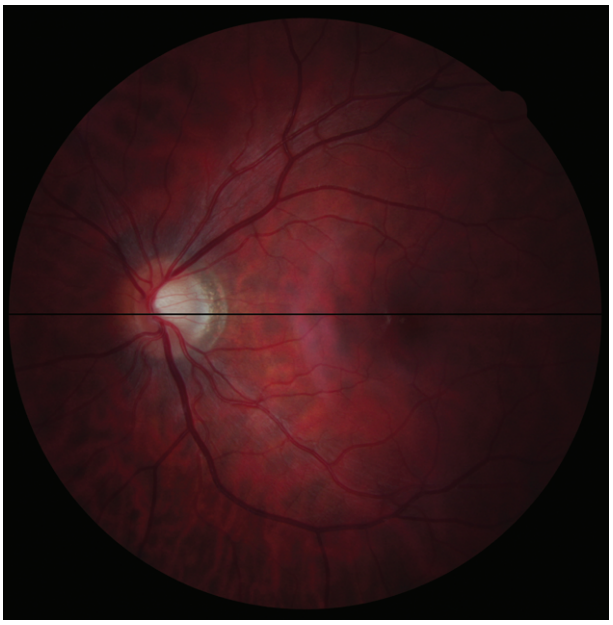

Figure 1: a) Example of one image from DRIIL database (image: kan_xx_L_10_12_2009_01.JPG)

2. METHOD DESCRIPTION

The method for illumination correction composes of two different parts: the first one deals with modeling of acquisition and correction model and the second one deals with estimation of the bias field.

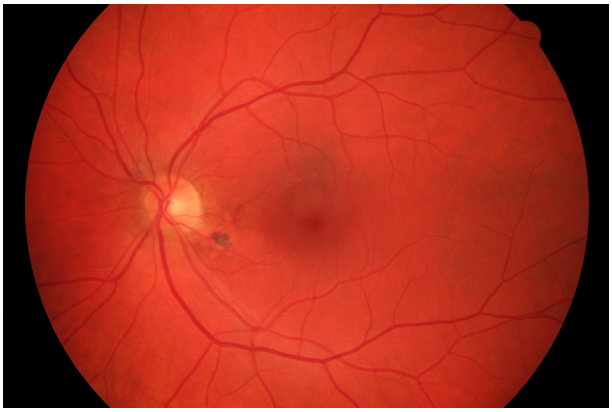

Figure 2: a) Example of low-contrast image of patient with diabetic retinopathy.

2.1 Acquisition and correction model

The model of image creation is needed for our purpose. We assume that each tissue (blood-vessels, optic disc, retinal surface) has a different mean value (depending on position (x,y)) $m(x,y)$ and corresponding characteristic texture, which can be modeled by the additive noise $n_{tiss}(x,y)$. The ideal output signal $o(x,y)$ therefore consists of piecewise constant values plus additive noise. Due to finite size of the point spread function $h(x,y)$ of the imaging device, the $o(x,y)$ is modified by convolution with $h(x,y)$ and with the thermal and electronic noise $n(x,y)$ generated by the device. The overall equation of the observed image $s(x,y)$ can be formalized as follows [7] (we omit the spatial indexes for simplicity):

$$s = [(m + n_{tiss}) \cdot b] * h + n \tag{1}$$

where b is the bias field in the range $(0,1)$. On the right hand side of equation (1), we can neglected the smoothing due to point spread function not playing a significant role in this problem:

$$s \approx o \cdot b + n. \tag{2}$$

Therefore, under this multiplicative assumption, we can estimate the original signal as [7]:

$$\hat{o} = \frac{s}{\hat{b}} - \frac{n}{\hat{b}} \approx \frac{s}{\hat{b}}, \tag{3}$$

where $\hat{b}$ is the estimated bias model. Here, we also neglect the noise term, because of the high quality of advanced digital detection sensors. The more practical equation should also include the correction of mean graylevel value [2]:

$$\hat{o} = \frac{s}{\hat{b}} - (b^{max} - 0.5). \tag{4}$$

The next modification of the last equation includes the red, green and blue (R,G,B) channel image. The RGB correction should be performed for each channel separately in the simplest case. To maintain the mean luminosity of each channel in corrected image, the mean value of each channel should be considered. The total mean image value μ_{RGB} is computed as a sum of the mean values from red, green and blue channel:

$$\mu_{RGB} = \mu_R + \mu_G + \mu_B \tag{5}$$

and the correction coefficients are given:

$$\kappa_R = \frac{\mu_R}{\mu_{RGB}}, \quad \kappa_G = \frac{\mu_G}{\mu_{RGB}}, \quad \kappa_B = \frac{\mu_B}{\mu_{RGB}}. \tag{6}$$

These coefficients are used for correction of respective channel (k = R,G,B) as:

$$\hat{o}_k = \frac{s_k}{\hat{b}_k} - \kappa_k(b_k^{max} - 0.5). \tag{7}$$

The last equation defines a straightforward technique for illumination correction.

2.2 Bias estimation

The modeling of the bias field $\hat{b}$ is based on bicubic B-spline surface [8]:

$$\hat{b}(x,y) = \sum_{i=0}^{3}\sum_{j=0}^{3} P_{ij} C_i(x) C_j(y), \tag{8}$$

where $\hat{b}(x,y)$ are points on the surface at position (x,y), P_{ij} are the control points and $C_i(x)$, $C_j(y)$ are the basis functions defined as:

$$C_0(t) = \frac{(1-t)^3}{6}, \quad C_1(t) = \frac{(3t^3 - 6t^2 + 4)^3}{6} \tag{9}$$

$$C_2(t) = \frac{(-3t^3 + 3t^2 + 3t + 1)^3}{6}, \qquad C_3(t) = \frac{t^3}{6}. \tag{10}$$

The retinal image is divided into defined patches O_n and for each patch the B-spline is determined. Several grid sizes were tested and we obtained good results with grid 12×12 for given images. The size of this grid depends on the image resolution and the field of view of the fundus camera (see below). It also determines the complexity of the surface spatial variations. The control points are determined by their z-values, z_n, at positions defined by the grid spacing. These are computed as averages from the pixel values in defined window around the control point positions, i.e.

$$z_n = \frac{1}{M.N} \sum_{x,y \in O_n} s(x,y), for n = 1,2,...144. \tag{11}$$

The size (M,N) of this window O_n has been experimentally set equal to the size of the patch. This approach gives three different illumination surfaces for R, G, B channel $(\hat{b}_R, \hat{b}_G, \hat{b}_B)$, which can be directly used for correction using equation (7).

3. EXPERIMENTAL EVALUATION

The proposed method has been tested subjectively on new high resolution fundus image set and objectively, using our previously published blood-vessel segmentation algorithm [9].

3.1 Subjective evaluation

The proposed algorithm was tested on the new publicly available fundus image database DRIIL (Digital Retinal Images for ILlumination correction) aimed for testing correction algorithms. The images and the results of illumination correction are made publicly available at

http://projects.ubmi.feec.vutbr.cz/ophthalmo. The database contains 165 high resolution fundus images (3888×2592 px) taken by digital camera Canon EOS 40D attached to Canon CR-1 fundus camera with 45 angle of view. The correction algorithm was applied to each channel separately, corrected RGB images were created and saved for subjective evaluation. An examples of estimated bias field used for correction is shown in Fig.3 together with correction by standard histogram equalization method. The intensity profiles of one row (depicted in corresponding fundus image in Fig. 1) are also shown.

This evaluation was based on a subjective assessment of the colour balance and the assessment of bias field before and after correction in RGB images. The separated RGB channels are merged together after correction in the same mean luminosity ratio, which helps to preserve the colour content of the image. In some cases, where the under-saturation of some colour channel is present (e.g. red channel), the corrected RGB image shows higher portion of colour from respective channels (e.g. green-blue) in that places. However, the blood-vessels contrast in these areas is significantly higher.

3.2 Objective evaluation

The proposed method has been evaluated as a preprocessing step in the blood-vessel segmentation framework described in [9]. We validated the influence of the non-uniform illumination correction on the accuracy of the blood-vessel tree segmentation using another database, which can be downloaded from www5.informatik.uni-erlangen.de/research/data/fundus-images. We have used two sets of images for testing from this database - dataset of healthy subjects (15 images) and dataset of diabetic patients (15 images). These images were manually segmented by a bioengineering expert, which resulted in a gold-standard images used for evaluation. The sensitivity, specificity and accuracy of segmentation algorithm were evaluated for each image with and without non-uniform correction step applied only to green channel (the segmentation algorithm works only with green channel [9]).

Table 1: Quantitative evaluation of the retinal blood-vessel segmentation method with non-uniform illumination (upper value) and without this preprocessing step (lower value). Higher values are boldfaced.

	Healthy subjects	DR patients	DRIVE [10]	STARE [11]
Sensitivity	78.64 **79.35**	73.58 **75.49**	70.67	69.44
Specificity	**97.38** 96.35	**95.29** 95.37	98.01	98.19
Accuracy	**95.29** 94.46	**94.46** 93.77	94.52	95.26

4. DISCUSSION AND CONCLUSION

The results were subjectively evaluated with respect to uniformity of illumination, visibility of blood-vessels in dark region (mainly at the periphery) and with respect to contrast of the blood-vessels. It can be concluded that for all images the enhancement of described properties can be observed. An example shown here demonstrate the successfulness of the proposed algorithm. The increase of the blood-vessel contrast is more visible in image profiles (as depicted in Fig. 3c). The comparison with standard histogram equalization (HE) technique is also shown. The HE method changes the red, green and blue channel luminosity and causes the contrast saturation.

The inspection of the segmentation results obtained with and without illumination correction shows a positive influence of this preprocessing step on the blood-vessels at the periphery of the image. Table 1 summarizes these results. In most cases, decrease of the segmented blood-vessels can be observed around and within the optic disc. This can be an advantage, because optic disc structure and visible nerve fibers are not segmented, which increases specificity. The sensitivity for DR patients is slightly decreased, but overall accuracy increased in comparison to accuracy obtained without the preprocessing step. These values have been compared to the currently published method [12], where the blood-vessel segmentation method achieved comparable accuracy on DRIVE [11] and STARE [10] databases. The comparison of these results obtained from other databases (with poor resolution images) is disputable, but the main aim of this comparison is to show the influence of the preprocessing step and comparability with existing method. It should be also noted that increasing the accuracy about 0.1% corresponds to accurate segmentation of 6920 pixels in our high resolution fundus images. Nevertheless, the results show that the segmentation results are to some extent robust to the bias.

The main purpose of the described bias field correction method is to increase the diagnostic content of fundus images based on their visual inspection. This is done mainly by increasing the object's contrast and by equalization of illumination throughout the image. The evaluation part is rather difficult because the subjective assessment of images. It can be concluded that the subjective perceiving of quality of corrected images was better for all tested images. Moreover, the luminosity of R,G,B channels is nearly maintained.

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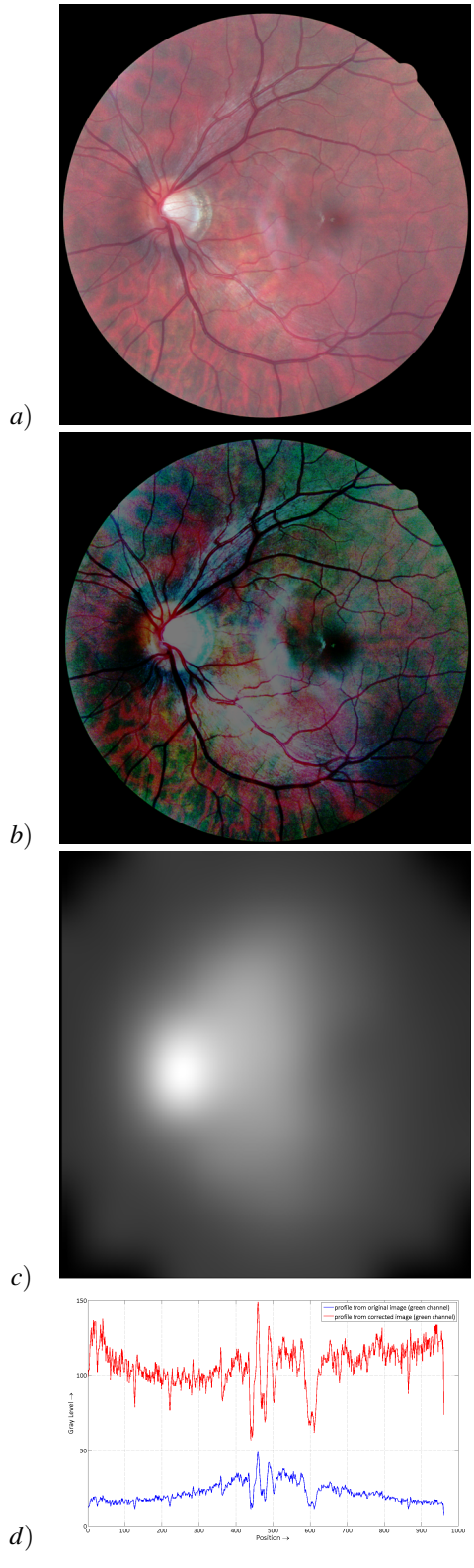

Figure 3: a) Image from Fig.1 corrected by proposed approach, b) Image corrected by histogram equalization, c) Estimated surface for correction, d) Intensity profile from one row depicted on Fig.1. (lower/blue curve - image profile from original image; upper/red curve - image profile from corrected image)

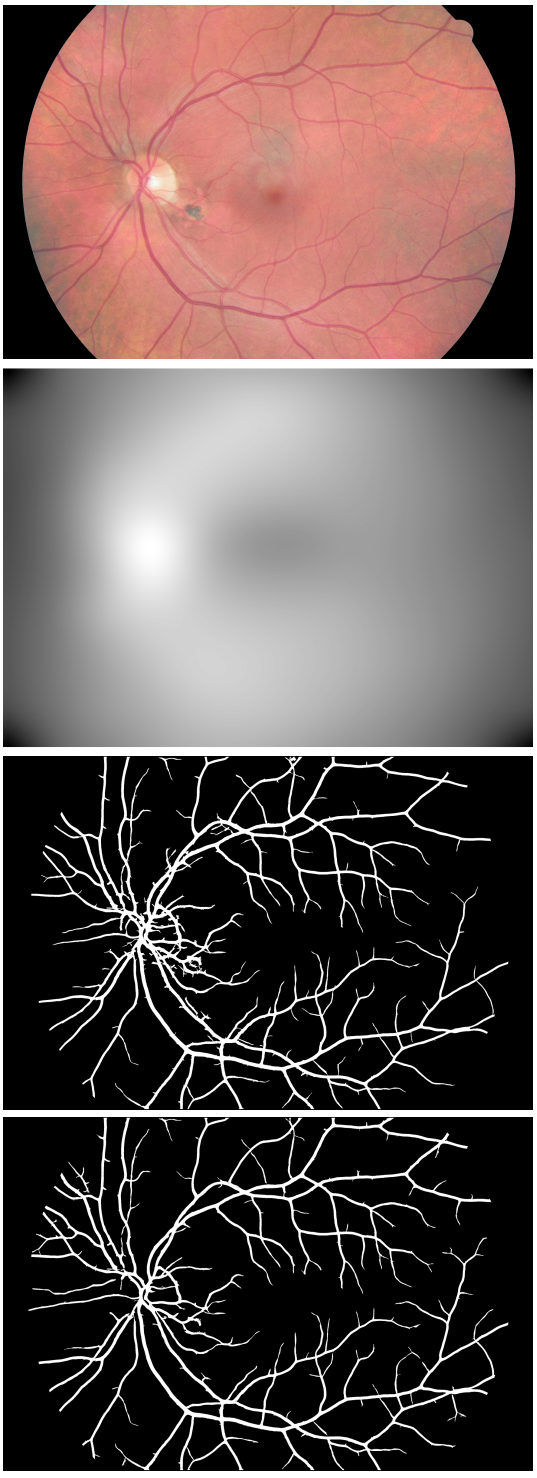

Figure 4: a) Image from Fig.2 corrected by proposed approach, b) Estimated bias for correction, c) Blood-vessel segmentation obtained without preprocessing using non-uniform illumination correction, d) Blood-vessel segmentation obtained with preprocessing step using non-uniform illumination correction.