Retrospective Illumination Correction of Retinal Images

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Abstract. A method for correction of non-homogenous illumination based on optimization of parameters of B-spline shading model in respect to the Shannon's entropy is presented. An analytical gradient term of the entropy criterion has been derived allowing to use the efficient L-BFGS optimization algorithm. The method has been tested on the set of 20 retinal images and has shown ability to substantially eliminate the illumination distortion. The application of this method for reliable image segmentation or registration was tested.

1 Introduction

Improper scene illumination as well as non-ideal acquisition conditions like inaccurate imaging system can introduce severe distortions into the final image. These distortions are usually perceived as smooth intensity variations across the image. For the case of retinal images the non-homogenous illumination is caused especially by vignetting effect and non-linear shading, see Fig. 1A). Under these conditions, the subsequent image processing like image segmentation or patter recognition is substantially hindered. In this contribution, we describe an algorithm for retrospective shading correction of retinal images.

2 Methods

For the purpose of illumination correction we need a model of imaging process. We assume, that each type of tissue class $k(\mathbf{x})$ (vessels, optic disc, retina surface) has a different value $r(\mathbf{x})$ of the property measured by the imaging device. Of course, every class of tissue has a characteristic texture, which can be modelled by noise addition $n_{tiss}(\mathbf{x})$. The ideal output signal $o(\mathbf{x})$ therefore consists of piecewise constant values with additive noise. Due to finite size of the point spread function of the device (different from ideal Dirac pulse), this ideal signal is further corrupted by convolution with the distortion point spread function $h(\mathbf{x})$ and with noise added by the device $n_{dev}(\mathbf{x})$. The overall equation of the imaging device model can be formalized as follows ($b(\mathbf{x})$ being the illumination):

$$s(\mathbf{x}) = \left[\left(o(\mathbf{x}) + n_{tiss}(\mathbf{x})\right) * h(\mathbf{x})\right] b(\mathbf{x}) + n_{dev}(\mathbf{x}) \approx o(x) \cdot b(\mathbf{x}) + n(\mathbf{x}).$$

Further on, we neglect the PSF of the imaging device and put both random variables into one term $n(\mathbf{x})$. Under assumption, that the bias involved in image creation process is multiplicative, we can reconstruct the original signal

$$\hat{o}(\mathbf{x}) = \frac{s(\mathbf{x})}{\hat{b}(\mathbf{x})} + \frac{n(\mathbf{x})}{\hat{b}(\mathbf{x})} = \frac{v(\mathbf{x})}{\hat{b}(\mathbf{x})} = v(\mathbf{x})\hat{b}^{-1}(\mathbf{x}),$$

where $v(\mathbf{x})$ is the observed signal, $\hat{b}(\mathbf{x})$ is the optimal illumination bias model, $\hat{b}^{-1}(\mathbf{x})$ is its reciprocal value. The choice of proper bias model $b(\mathbf{x})$ as well as an appropriate cost function, describing how well the non-homogenous illumination of the image is corrected for current parameters of the bias model, is crucial. In [1], Likar et al. used polynomial multiplicative and additive shading model, the parameters of which were optimized using Powell optimizer in respect to the cost-function based on image entropy. Authors of [2] modelled the bias field using Legendre polynomials and used an energy function based on the multi-class model estimator, the parameters of the bias model optimal in respect to this criterion have been found 1+1 evolutional search algorithm.

Bias model

Generally, the intensity transformation performed by the reciprocal bias model can be defined as a linear combination of K smooth basis functions $s_i(\mathbf{x})$.

$$\hat{b}^{-1}(\mathbf{x}) = \sum_{i=1}^{K} \mathbf{\Phi}_i s_i(\mathbf{x}),$$

where $\mathbf{\Phi}_i$ are the parameters of the transform defining the contribution of each basis.

Similarly to [1], we introduce the mean preserving condition in order to avoid a global shift of mean intensity of the resultant corrected image. Further, as we use the multiplicative bias model, the influence of each parameter on the final intensity is dependent on its value. Therefore, we introduce a normalization constraint for every base function kernel $s_i(\mathbf{x})$. The mathematical definition of both these conditions can be found in [1].

We have found that the illumination distortion of the retinal images is partially local, but both mentioned models have global character influencing the whole image despite the locally defined distortion (e.g. the image is corrupted in its upper left corner only, but the polynomial model significantly influences the opposite corner as well). Hence, we decided to newly use the locally defined mean corrected and normalized bias model based on B-splines formalized as follows:

$$\hat{b}^{-1}(\mathbf{x}) = \sum_{\mathbf{x}_i \in V} \mathbf{\Phi}(\mathbf{x}_i) \left[\left(\beta^{(n)}\left(\frac{\mathbf{x}}{\mathbf{h}} - \mathbf{x}_i \right) - c^m(\mathbf{x}_i) \right) \Big/ c^n(\mathbf{x}_i) \right],$$

where, for the case of two dimensions, $\beta^{(n)}(\mathbf{x}) = \beta^{(n)}(x_1) \cdot \beta^{(n)}(x_2)$ is a separable n^{th} order B-spline convolution kernel, $\mathbf{h}$ is the spacing of the control points grid (can be different but constant for each dimension), coefficients $\Phi(\mathbf{x}_\text{i})$ corresponding to the control point are the parameters of the bias model, $c^m(\mathbf{x}_\text{i})$ are coefficients ensuring the mean conservation condition and $c^n(\mathbf{x}_\text{i})$ are coefficients ensuring normalization of the parameters; both these coefficients are pre-computed before shading correction. Details can be found in [1].

Cost function

In order to find the parameters of the bias model eliminating the undesirable illumination, we need to define a criterion, with respect to which the parameters could be optimized. In Likar [1] the image entropy is proven as suitable criterion. The idea is, that the illumination is an additional information added to the information included in the original signal o($\mathbf{x}$) and because we would like to remove the illumination bias, the information content of the corrected image should be lower than the information content of the distorted image v($\mathbf{x}$). Therefore, when looking for parameters of bias model eliminating the non-homogenous illumination, we minimize the Shannon's entropy H(.) of the image which is measure of the information amount. Thus,

$$H(\kappa) = -\sum_{\kappa} p(\kappa)\log(p(\kappa)), \quad \text{where } p(\kappa;\mathbf{\Phi}) = \alpha \sum_{\mathbf{x}_i \in V} \beta^{(3)}\left(\frac{v(\mathbf{x}_i;\mathbf{\Phi})}{s} - \kappa \right)$$

is the probability estimate of appearance of intensity value κ, which is obtained using Parzen windowing (PW) method for histogram evaluation, $\beta^{(3)}$ is 3rd order B-spline kernel, s is a parameter defining the size of the histogram bin and $\alpha = 1/\Theta$ is a normalization coefficient assuring that the sum of $p(\kappa)$ is equal to one.

Optimization

The overall illumination correction algorithm consists in looking for parameters of mentioned B-spline bias model b^{-1} minimizing the entropy criterion H and is formalized as

$$\mathbf{\Phi}_{\text{opt}} = \arg\min_{\mathbf{\Phi}} \left\{ H\left(v(\mathbf{x}) b^{-1}(\mathbf{x}) \right) \right\}$$

Thanks to our formulation of the criterion based on PW, both the probability estimation and the intensity transformation are defined continuously and therefore we could newly derive the analytical form for the criterion differentiation with in respect to components of the parameter vector $\mathbf{\Phi}$:

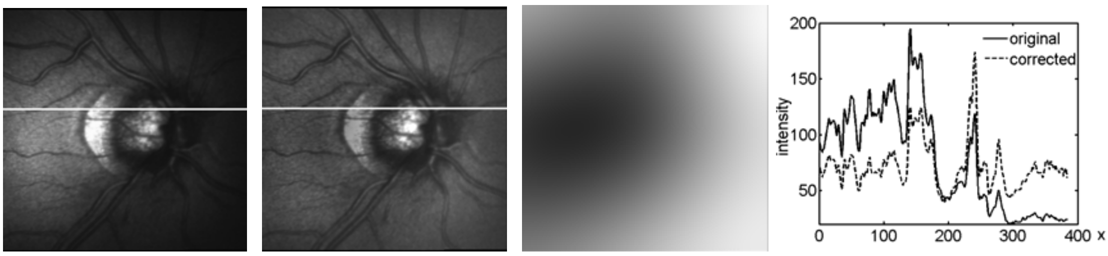
$$\frac{\partial H(\kappa;\mathbf{\Phi})}{\partial \mathbf{\Phi_k}} = -\sum_{\kappa} \frac{\partial p(\kappa;\mathbf{\Phi})}{\partial \mathbf{\Phi_k}}\left(\log\left(p(\kappa)\right)+1\right), \text{ where}$$

$$\frac{\partial p(\kappa;\mathbf{\Phi})}{\partial \mathbf{\Phi_k}} = \alpha \sum_{\mathbf{x}_i \in V} \left.\frac{\partial \beta^{(3)}(\xi)}{\partial \xi}\right|_{\xi=\frac{v(\mathbf{x})b^{-1}(\mathbf{x})}{s}-\kappa} v(\mathbf{x})\beta^{(3)}\left(\frac{v(x_{i1})}{h_1}-k_1\right)\beta^{(3)}\left(\frac{v(x_{i2})}{h_2}-k_2\right).$$

Hence, we are able to use very efficient L-BFGS algorithm for high dimensional optimization. The details of the derivation should be discussed in a journal paper under preparation.

3 Results

The proposed algorithm has been tested on a series of 20 retinal images obtained by means of HRTII confocal scanning laser ophthalmoscope and colour fundus camera Kowa. On Fig. 1, a result of the algorithm applied to a real retinal image is illustrated; the intensity profiles clearly show the successful bias correction.



A B C D

Fig. 1. A: Retinal image highly corrupted by non-homogenous illumination, B: Image after multiplicative correction by recovered bias field, C: Normalized bias field controlled by 3x3 parameters automatically obtained using proposed algorithm, D: Intensity profiles along the indicated row.

According to our first tests, the proposed algorithm has shown positive influence to reliability of registration of retinal images using the registration method developed by our group [4].

4 Conclusions

The method for efficient illumination correction was proposed and qualitatively verified, using an optimal B-spline shading model found via the L-BFGS optimizer and a newly derived analytical gradient of the Shanon entropy criterion. The proposed algorithm should be further widely tested on the retinal images database in the near future.

Acknowledgement

This project is running under the support of the research centre DAR (sponsored by the Ministry of Education, Czech Republic), project no. 1M6798555601.

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