

On the Compensation of Uneven Illumination in Retinal Images for Restoration by Means of Blind Deconvolution

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Abstract

Retinal eye fundus images are used for diagnostic purposes, but despite controlled conditions in acquisition they often suffer from uneven illumination and blur. In this work, we propose the use of multi-channel blind deconvolution for the restoration of blurred retinal images. The estimation of an adequate point-spread function (PSF) is highly dependent on the registration of at least two images from the same retina, which undergo illumination compensation. We use the bi-dimensional empirical mode decomposition (BEMD) approach to model the illumination distribution as a sum of non-stationary signals. The BEMD approach enables an artifact-free compensation of the illumination in order to estimate an adequate PSF and carry out the best restoration possible. Encouraging experimental results show significant enhancement in the retinal images with increased contrast and visibility of subtle details like small blood vessels.

1. Introduction

Blur is one of main image quality degradations in eye fundus images. Its main causes are: inherent optical aberrations in the eye, relative camera-eye motion, and improper focusing. The optics of the eye is part of the optical imaging system and as such, eye aberrations are a common source of image degradation. The technique for recovering an original or unblurred image from a single or a set of blurred images in the presence of a poorly determined or unknown point spread function (PSF) is called blind deconvolution. For the restoration of retinal images, we have proposed [4] a blind deconvolution method to restore blurred retinal images acquired several months apart, even when structural changes had occurred in the retina.

Our restoration approach is based on multi-channel blind deconvolution (MBD) [7]. MBD requires at least two

images of the same scene in order to recover the PSFs and carry out the restoration. We consider as input two retinal images acquired with a conventional fundus camera within a time lapse that can span from several minutes to months given by routine patient checkups. The images correspond to the same retina but can differ with respect to illumination distribution, blur, and local structural changes given by pathological developments. These differences cannot solely be accounted for by the convolutional model. For that reason, the images must be preprocessed before the blind deconvolution stage can take place. We register the images and compensate for uneven illumination variation. Our work builds upon [4], the illumination distribution is compensated by making the illumination of one image as close as possible to the other image. This has a clear advantage of being easier to compute, but it does not guarantee a uniform illumination that provides better definition and contrast of the retinal image, despite improving PSF estimation.

In order to compensate the non-uniform illumination of retinal images the illumination distribution has to be estimated properly. However, this is not straight-forward since the retina has several elements like the blood vessels or the optic disc, which have different luminosity properties. Thus, a proper illumination compensation approach should take this into account. Illumination compensation is important not only for visualization purposes, but also often included in the pipeline of algorithms for automated digital image analysis [5, 2], for disease detection [1], for image restoration or deconvolution [3], and longitudinal change detection

2. Mathematical Model of Image Degradation

The unregistered input images, as shown in Figure 1, are \hat{I}_1 and \hat{I}_2 . After registration, we obtain two degraded registered images I_1 and I_2 , which we model as originating from an ideal sharp image. Mathematically, the degradation

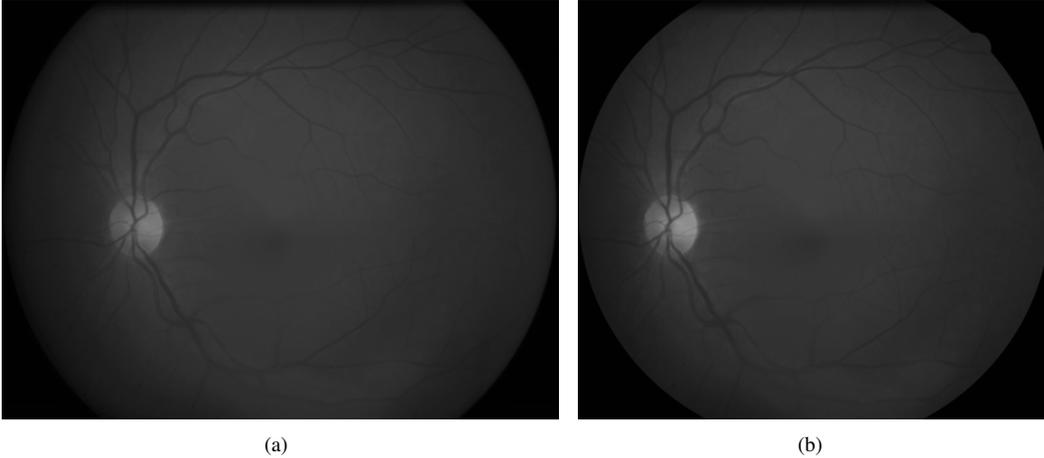


Figure 1. Two fundus images from the same retina. Both are degraded with blur and uneven illumination.

model is stated as

$$\begin{aligned} I_1 &= U * h_1 + n_1 \\ I_2 &= U * h_2 + n_2 \end{aligned} \quad (1)$$

where $*$ is the standard convolution, h_i are called convolution kernels or PSFs, and n_i are Gaussian zero-mean noise.

3. Bidimensional Empirical Mode Decomposition (BEMD)

BEMD is a two-dimensional (2-D) extension of the classical EMD [6]. The EMD method is a sifting process that decomposes any complex signal into a finite, and often small, number of components called intrinsic mode functions (IMFs). An IMF represents a simple oscillatory mode with the same number of extrema and zero crossings, with its envelopes being symmetric with respect to zero.

In BEMD an image $I(x, y)$ is decomposed into multiple IMFs by the following sifting process:

1. Initialization: set $S(x, y) = I(x, y)$.
2. Identify all local maxima and local minima of $S(x, y)$.
3. Interpolate the local maxima (resp. minima) to obtain the upper envelope $e_{\max}(x, y)$ (resp. lower envelope $e_{\min}(x, y)$).
4. Compute the mean envelope $m(x, y) = [e_{\max} + e_{\min}] / 2$.
5. Compute $S'(x, y) = S(x, y) - m(x, y)$.
6. Update $S(x, y)$ by $S'(x, y)$.

Repeat steps 1 to 5 until the stopping criterion is met, in this case by limiting the size of the standard deviation (SD)

computed from two consecutive sifting iteration results as:

$$SD = \frac{\sum_x \sum_y [S'(x, y) - S(x, y)]^2}{\sum_x \sum_y [S(x, y)]^2} \quad (2)$$

This sifting process stops if SD is less than a threshold. The resulting $S'(x, y)$, denoted by $c_1(x, y)$, is considered as the first IMF which represents the fast fluctuating component of the image. The residue $r_1(x, y) = I(x, y) - c_1(x, y)$ is a slower fluctuating signal, which is treated as the new input, i.e. $S(x, y) = r_1(x, y)$. The same sifting is then applied to the new input to extract the next IMF and produce the next residue. This iteration is carried out n times until no more IMFs can be extracted. Consequently, the original image can be obtained by:

$$I(x, y) = \sum_{j=1}^n c_j(x, y) + r_n(x, y) \quad (3)$$

4. Illumination Compensation by BEMD

In this paper we propose the use of BEMD to accurately estimate the illumination distribution of retinal images. BEMD has the advantage that it decomposes the image in a nonlinear way into IMFs. The first IMF contains the highest spatial frequencies, the other IMFs contain frequencies progressively smaller and the residue represents low-frequency information in the source image.

After decomposing the image into IMFs, the residue contains the smoothest transitions in the image. We can model these as the changes in illumination. In this way, because the residue also has the dc content of the original image, we can proceed to compensate the illumination in the retinal image by subtracting the residue from the original image. From Eq. (3) the compensated image is

$$I'(x, y) = I(x, y) - r_n(x, y) \quad (4)$$

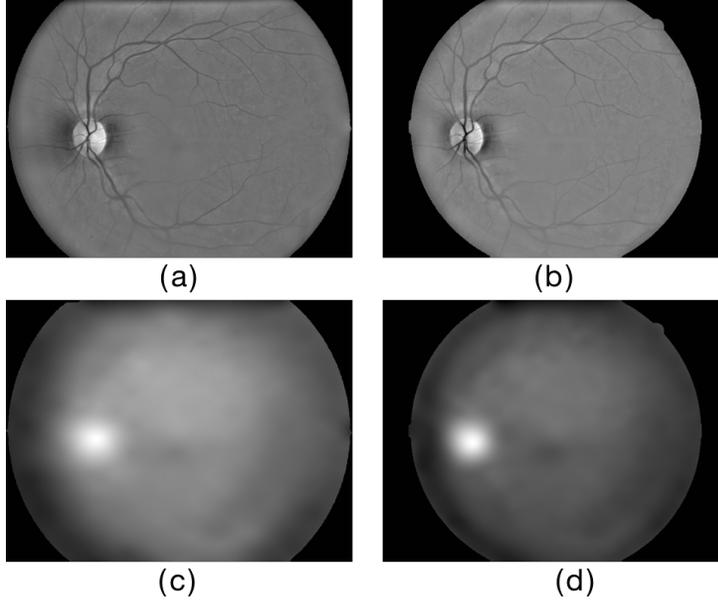


Figure 2. Illumination compensation by means of BEMD. (a)-(b) Are the compensated images from Figure 1. (c)-(d) are the residue (illumination component). Notice the increase in contrast and the uniform illumination.

5. Image restoration

The PSF estimation and image deconvolution algorithm can be viewed as a Bayesian maximum a posteriori estimation of the most probable sharp image and blur kernels. The algorithm is basically the minimization of the functional

$$\arg \min_{U, h_1, h_2} \frac{1}{2} \|U * h_1 - I'_1\|^2 + \frac{1}{2} \|U * h_2 - I'_2\|^2 + \lambda_u \int |\nabla U| + \lambda_h \|I'_1 * h_2 - I'_2 * h_1\|^2, \quad (5)$$

$$h_1, h_2 \geq 0,$$

with respect to the latent image U and blur kernels h_1 and h_2 . The first and second terms measure the difference between the input blurred images and the searched image U blurred by kernels h_1 and h_2 . The size of this difference is measured by L_2 norm $\|\cdot\|$ and should be small for the correct solution. Ideally, it should correspond to the noise variance in the given image. I'_i are the illumination compensated images. The two remaining terms are regularization terms with positive weighting constants λ_u and λ_h . The third term is the total variation of U . It improves stability of the minimization and from the statistical viewpoint incorporates prior knowledge about the solution. The last term is a condition linking the PSFs of both images, which also improves the numerical stability of the minimization. For this procedure we set $\lambda_u = 1000$ and $\lambda_h = 10$.

The functional is alternately minimized in the subspaces corresponding to the image and the PSFs. The minimization in the PSF subspace is equivalent to the solution of a system of linear equations in the least squares sense with the non-

negativity constraint. In the same minimization procedure both the PSFs and the restored image are estimated.

6. Experiments and Results

We performed several experiments on naturally degraded images coming from the clinical practice to illustrate the appropriateness of the method. The proposed method has been tested on a dataset of 20 images with reliable results. In this section we show two typical examples of retinal images degraded with uneven illumination, their compensation, and the restoration by means of MBD.

In Figure 2 we show the same retinal images from Figure 1 with the illumination compensation by BEMD. It is important to highlight the increase in contrast and the homogeneous illumination. Figure 2(c)-(d) show the estimated illumination distribution.

In Figure 3 we show a detail of the restored retinal image by deconvolution and the estimated PSFs. There is a notable increase in visibility of subtle details like small blood vessels.

7. Conclusions

In this work we have proposed the use of the bidimensional empirical mode decomposition as a means of compensation of uneven illumination prior to restoration by multichannel blind deconvolution. The compensation of the illumination provided an improvement in contrast and a homogeneous illumination. In addition, the restoration by deconvolution improves visibility of subtle details like small blood vessels.

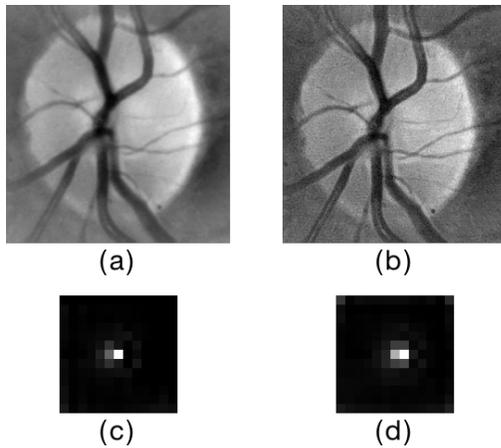


Figure 3. Image restoration by MBD. (a) original image with illumination compensation by BEMD. (b) Restored image. (c)-(d) Estimated PSFs for images in Fig. 2 (a)-(b). Note at the increase in visibility of small blood vessels.

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References

- [1] M. U. Akram, S. Khitran, A. Usman, and U. Yasin. Detection of Hemorrhages in Colored Fundus Images Using Non Uniform Illumination Estimation. In A. Campilho and M. Kamel, editors, *Lecture Notes in Computer Science*, volume 8815, pages 329–336. Springer International Publishing, 2014.
- [2] Y. Lu, F. Xie, Y. Wu, Z. Jiang, and R. Meng. No Reference Uneven Illumination Assessment for Dermoscopy Images. *IEEE Signal Processing Letters*, 22(5):534–538, 2015.
- [3] A. G. Marrugo and M. S. Millan. Retinal Image Analysis Oriented to the Clinical Task. *Electronic Letters on Computer Vision and Image Analysis*, 13(2):54–55, 2014.
- [4] A. G. Marrugo, M. Sorel, F. Sroubek, and M. S. Millan. Retinal image restoration by means of blind deconvolution. *Journal of Biomedical Optics*, 16(11):116016, 2011.
- [5] M. J. Newton. The promise of telemedicine. *Survey of Ophthalmology*, 59(5):559–567, Sept. 2014.
- [6] J. C. Nunes, Y. Bouaoune, E. Delechelle, O. Niang, and P. Bunel. Image analysis by bidimensional empirical mode decomposition. *Image and Vision Computing*, 21(12):1019–1026, Nov. 2003.
- [7] F. Sroubek and J. Flusser. Multichannel blind deconvolution of spatially misaligned images. *IEEE transactions on image processing : a publication of the IEEE Signal Processing Society*, 14(7):874–883, July 2005.