On the Illumination Compensation of Retinal Images by Means of the Bidimensional Empirical Mode Decomposition

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ABSTRACT

Retinal images are used for diagnostic purposes by ophthalmologists. However, despite controlled conditions in acquisition retinal images often suffer from non-uniform illumination which hinder their clinical use. In this work we propose the compensation of the illumination by modeling the intensity as a sum of non-stationary signals using bidimensional empirical mode decomposition (BEMD). We compare the estimation and compensation of the background illumination with a widely used technique based retinal image pixel classification. The proposed method has shown to provide a better estimation of the background illumination, particularly in complicated areas such as the optic disk (usually bright) and the periphery of fundus images (usually dim).

Keywords: Medical image, retinal image, illumination compensation, empirical mode decomposition, fundus photography, ophthalmology, image enhancement.

1. INTRODUCTION

Eye fundus photography documents the retina and is central to the clinical care and management of patients with retinal diseases. It is widely used for population-based, large scale detection of diabetic retinopathy, glaucoma, age-related macular degeneration, and other eye-related diseases.[1] Retinal images, with typical angle of view of 30°, are acquired with a digital fundus camera which captures the illumination reflected from the retinal surface. Despite controlled conditions, many retinal images suffer from non-uniform illumination caused by several factors; e.g., the curved surface of the retina, pupil dilation (highly variable among patients), the presence of diseases, among others.[2] Generally, the curved retinal surface and the geometrical configuration of the light source and camera lead to a poorly illuminated peripheral part of the retina with respect to the central region. A retinal image with uneven illumination is shown in Figure 1(a). Note how the periphery is poorly illuminated.

Several techniques have been used to enhance retinal images. Histogram equalization has been shown to be inappropriate for retinal images.[3] A local normalization of each pixel to zero mean and unit variance aims to compensate lighting variation and enhance local contrast but also introduces artifacts.[3] Histogram matching between the red and green planes has been used as a preprocessing step for vessel segmentation.[4] This improves the contrast of gross dark features like vessels but reduces the contrast of bright objects and tiny dark objects like micro-aneurysms. While most of the aforementioned methods are motivated by automated analysis as a preprocessing stage, they are all formulated without domain knowledge of the characteristics of the retinal image, and several despite increasing contrast and overall brightness introduce artifacts.

In order to compensate the non-uniform illumination of retinal images the illumination distribution has to be estimated properly. However, this is not straightforward 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,[6,7] for disease detection,[8] for image restoration or deconvolution,[9] and longitudinal change detection.[10]

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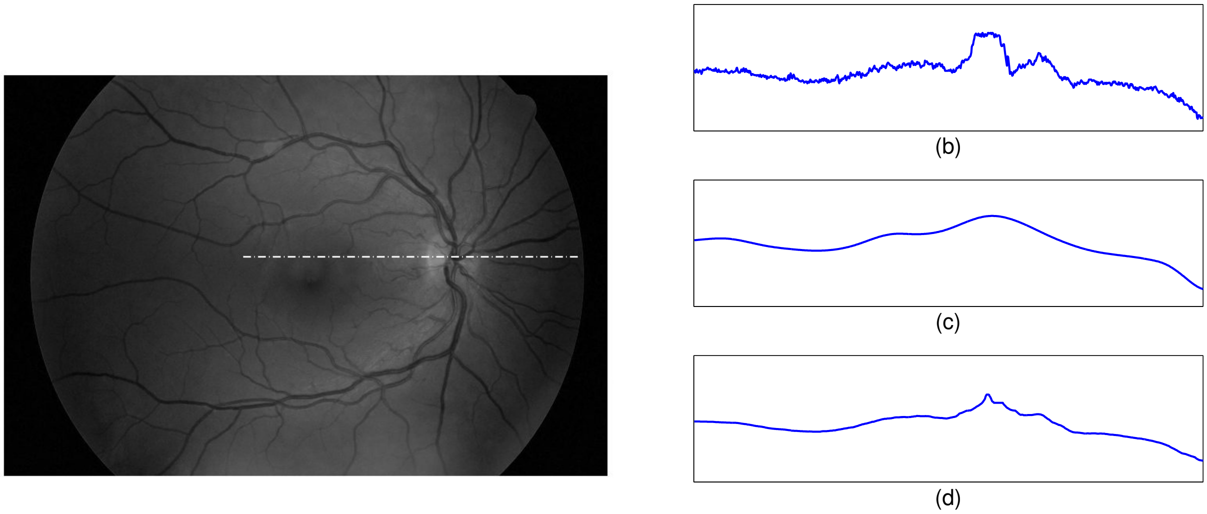


(a)

Figure 1. (a) Original retinal image with non-uniform illumination. Note that the illumination is worse toward the periphery of the image. (b) Intensity profile from image (dashed line in (a)) that goes across the optic disc. (c) Background illumination estimation with EMD. (d) Background illumination estimation from Ref. 5.

2. MOTIVATION AND RELATED WORKS

The work of Foracchia et al.[5] was one of the first to propose a strategy that allowed the estimation of the background luminosity distribution solely from the *background pixels* of the retinal image. Their method separates the image into background and foreground planes using a windowing approach. The blood vessels and the optic disc belong to the foreground. This is a valid assumption as long as the classification of pixels is correct. If the pixels from the optic disc are classified as belonging to the background the illumination distribution is not estimated properly. This has been pointed out by Marrugo and Millán,[11] and recently in Ref. 8.

The work of Foracchia et al.[5] introduced a strategy for luminosity and contrast enhancement on each color plane of the RGB color space, independently. This approach often produced hue-shifting related artifacts, given by the introduction of new colors to the image. Joshi et al.,[12] proposed a strategy that would avoid the color artifacts by performing the enhancement on single color plane to compensate equally every channel and ultimately perform linear color remapping. In this paper we work directly with the green channel of the RGB fundus image because it provides the best contrast.[9] This is mainly due to the spectral absorption of the blood in this band, which yields the dark and well contrasted blood vessels.[13] We also work with intensity fundus images like in the case of a retinal angiography as shown in Figure 5.

If we take an intensity profile along a row of the retinal image, like the one corresponding to the dashed line of Figure 1(a) and shown in Figure 1(b), we notice that the optic disc is a bright region that does not have the same properties or image statistics of the rest of the image. Moreover, the approach of Foracchia et al.[5] uses the Mahalanobis distance to determine whether a pixel belongs to the background by using a fixed threshold. Akram et al.[8] determined that a fixed threshold is not efficient due to the large variability of illumination and contrast in intra/inter image. This problem has been typically circumvented with additional stages of processing to better classify background pixels.[14,15] In this paper we take a different approach by modeling the intensity profile as a sum of non-stationary signals using empirical mode decomposition (EMD).[16]

In Figure 1(d) we show the background estimation from the profile in Figure 1(b) following the method of Foracchia et al.[5] On the one hand, note that while the profile follows the same general tendency of the original profile, the region sorrounding the optic disc (the peak of the profile) is not smooth enough as it would be expected if only non-uniform illumination effects were involved. On the other hand, the profile in Figure 1(c) was obtained by EMD and it is much smoother around the optic disc.

3. BIDIMENSIONAL EMPIRICAL MODE DECOMPOSITION (BEMD)

BEMD is a two-dimensional (2-D) extension of the classical EMD.[17] 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

$$\mathrm{SD} = \frac{\sum_x \sum_y \left[S'(x, y) - S(x, y)\right]^2}{\sum_x \sum_y \left[S(x, y)\right]^2} \ . \tag{1}$$

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:

$$I(x, y) = \sum_{j=1}^{n} c_j(x, y) + r_n(x, y) \ . \tag{2}$$

The decomposition by sifting process of an image provides a representation that is easy to interpret. In Figure 2 we show the EMD decomposition of the intensity profile from Figure 1(b). Note that the first IMF has all the local space-varying high frequency content from the original signal. The other IMFs contain smaller frequencies up to the residue which represents the smoothest variations in the image.

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 IMS 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.

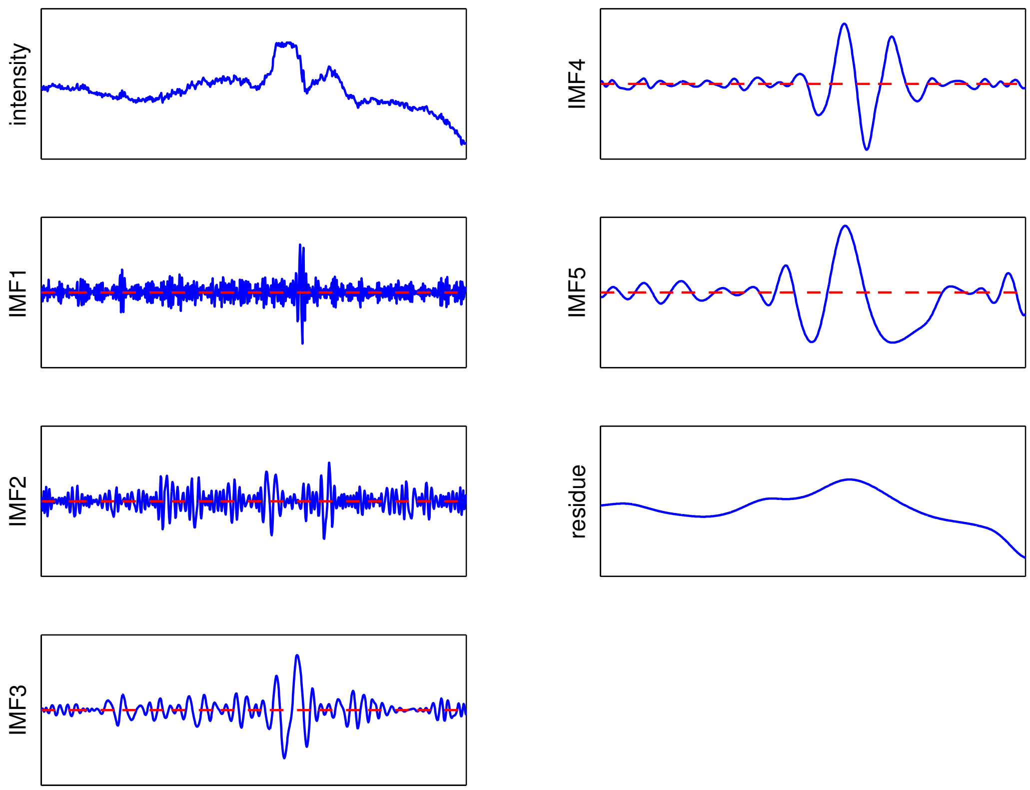


Figure 2. Empirical Mode Decomposition of the intensity profile plotted in Figure. 1(b).

4.1 Implementation

The BEMD algorithm was developed in MATLAB. To carry out a fast sifting procedure the algorithm searches for the maxima and minima by rows, columns, and diagonals. To compute the lower and upper envelopes it estimates a 2D surface on a 2D grid based on the scattered data from the local minima and maxima using the code from Ref. 18. The 2D surface estimation is not an interpolation, instead it is a regularized estimation in a least squares adjustment that smoothens the surface by keeping the surface gradients as small as possible. The stopping threshold for the sifting process was set at SD ≤ 0.2.

Despite our fast maxima/minima search, the surface fitting algorithm takes considerable time to compute. To this end, we estimated the residue on a low-resolution version of the original image (512×512). This approximation does not introduce much error in the estimation because illumination variations are smooth and preserved through subsampling. We scaled back the residue to the original resolution and perform the compensation. The typical execution time for a retinal image of 2000×1500 pixels on MATLAB R2014 running on a PC with a core i5 processor and 8 GB of RAM is 3 minutes.

5. 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 and their compensation.

For the purpose of illustration in Figure 3 we show the compensation of the non-uniform illumination in 1D from the intensity profile from Figure 1(b) using the compensation by BEMD (Figure 3(b)) and following the approach in Ref. 5 (Figure 3(c)). Note how the profile in the optic disc region is highly distorted in Figure 3(c) when compared to the original profile. However, the illumination distribution is indeed much more uniform. The

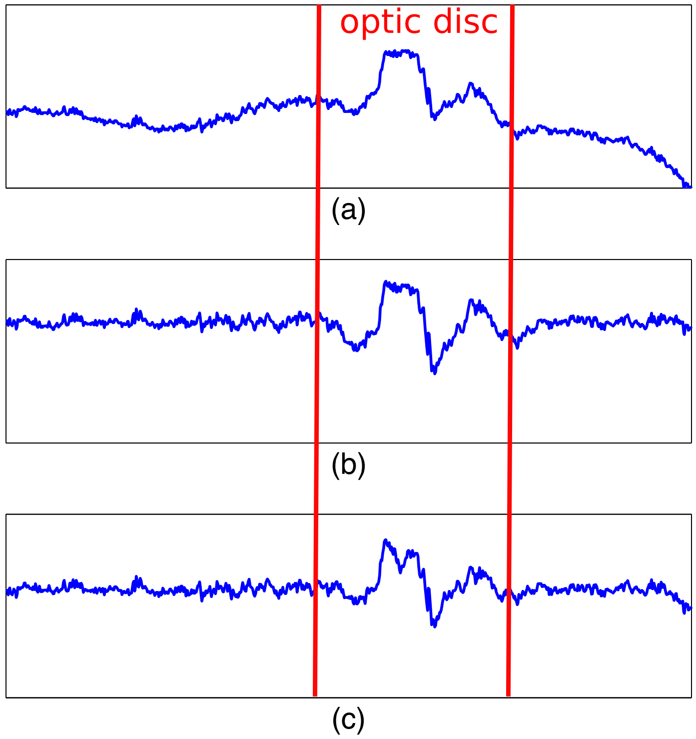


Figure 3. Compensation of non-uniform illumination. (a) Original intensity profile. (b) Compensation by EMD. (c) Compensation following Ref. 5

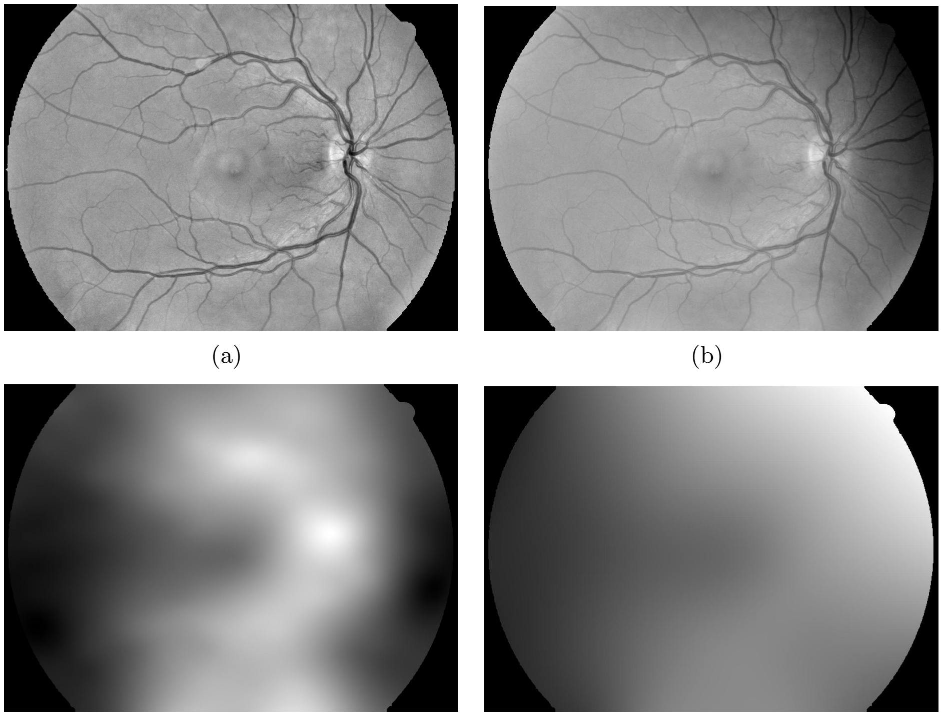
compensation shown in Figure 3(b) distorts less the optic disc region and has a uniform illumination distribution, represented in a more flat profile.

In Figure 4(b) we show the compensated retinal image of Figure 1(a) using the method from Ref. 5. Note how the peripheral illumination has not been compensated properly. This is due to an incorrect pixel classification. If the area surrounding the optic disc alters the classification, then the background illumination estimation fails. In contrast, the compensated image by BEMD shown in Figure 4(a) has been significantly enhanced with a uniform illumination distribution. In Figures 4(c)(d) we show the background illumination estimation from each corresponding method. In Figure 4(c) we note that it represents the smooth changes in the image while maintaining the local nature of the illumination distribution. The other estimation fails to reproduce the local variation.

A second example is given in Figure 5 where we show the compensation of a retinal angiography. The illumination is uniform and the blood vessels can be better appreciated in the compensated image along with other retinal features.

6. CONCLUSIONS

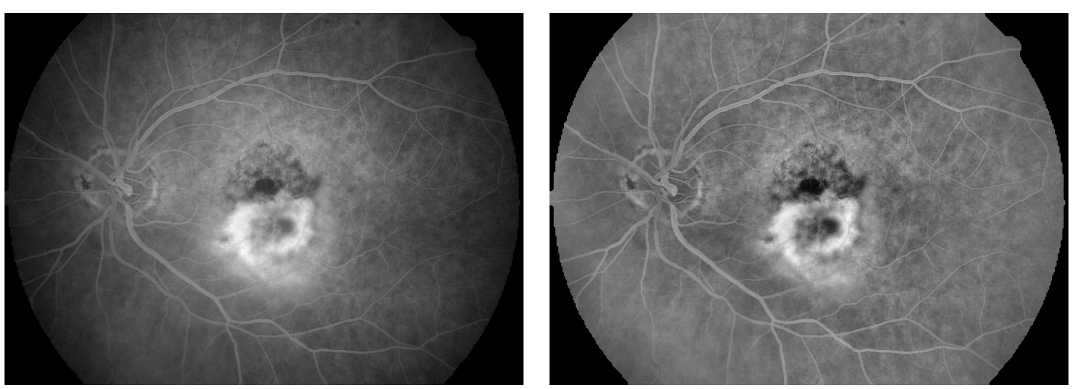
In this work we have presented a method for the estimation and compensation of the non-uniform illumination in retinal images by means of the bidimensional empirical mode decomposition. The method has shown to provide a better estimation of the background than related works, particularly in complicated areas such as the optic disk (usually bright) and the periphery of fundus images (usually dim). Two examples consisting of a fundus image and an angiography have been taken to design and illustrate the application of the method. Some improvement to speed up the computation is recommendable before its application to clinical studies.



(a) (b)

(c) (d)

Figure 4. Illumination estimation and compensation for retinal image in Figure 1(a). Compensated retinal image by (a) BEMD and (b) following Ref. 5 (c) Background illumination estimation with BEMD. (d) Background illumination estimation from Ref. 5.



(a)

Figure 5. (a) A retinal angiography with non-uniform illumination. (b) Compensated image by BEMD.

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