Retinal image analysis: preprocessing and feature extraction

To cite this article: Andrés G Marrugo and María S Millán 2011 J. Phys.: Conf. Ser. 274 012039

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Retinal image analysis: preprocessing and feature extraction

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Abstract. Image processing, analysis and computer vision techniques are found today in all fields of medical science. These techniques are especially relevant to modern ophthalmology, a field heavily dependent on visual data. Retinal images are widely used for diagnostic purposes by ophthalmologists. However, these images often need visual enhancement prior to apply a digital analysis for pathological risk or damage detection. In this work we propose the use of an image enhancement technique for the compensation of non-uniform contrast and luminosity distribution in retinal images. We also explore optic nerve head segmentation by means of color mathematical morphology and the use of active contours.

Keywords – retinal image, medical imaging, eye fundus, optic disc.

1. Introduction
Over the last decade, color digital photography has been recognized as an acceptable modality for documenting retinal appearance as it provides vital information about the health of the sensory part of the visual system [1]. Automatic segmentation and analysis of retinal images can be used to detect pathological risk or damage, and to assist in diagnosis.

Digital image analysis techniques in retinal imaging span from preprocessing techniques for visual enhancement or for further processing and ultimately any sort of feature extraction or segmentation. This work aims to illustrate the relationship of the ensemble of these different techniques. The paper mainly consists of two parts: The first part deals with an enhancement technique to compensate for uneven illumination and poor contrast in retinal images. In the second, we develop a strategy for optic disc (OD) segmentation based on color mathematical morphology as a preprocessing stage.

2. Retinal image enhancement
Retinal images 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 given by several factors: the curved surface of the retina, pupil dilation (highly variable among patients), or presence of diseases, among others. 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 part (Figure 1(a)).

Several techniques have been used to enhance retinal images. Histogram equalization has been shown to be inappropriate for retinal images [2]. A local normalization of each pixel to
to belong to the background. The next step is to estimate the retinal structures, such as the OD and blood vessels, while the remaining pixels are considered the RGB retinal image because it is the component with highest contrast. Thus, in order to central region and dense in the periphery.

A similar type of non-uniform sampling grid shown in figure 1(b). The sampling is coarse in the illumination distribution that leads to less computational burden. Therefore, we decided to use grid, whereas in [5] they use a more intuitive sampling scheme based on the knowledge of the original image. The sampling approach of [6] divides the whole image into a square sampling grid, and (c) first principal component of (a) from PCA analysis.

Figure 1. (a) Retinal image with uneven illumination and contrast, (b) non-uniform sampling grid, and (c) first principal component of (a) from PCA analysis.

Color retinal image enhancement is required for human visual inspection or for the application of vector processing techniques. The work of Foracchia et al. [4] aimed to introduce a strategy for luminosity and contrast enhancement on each color plane of the RGB color space, independently. This approach tended to produce hue-shifting related artifacts, given by the introduction of new colors to the image. More recently, Joshi et al. [5], 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. Our approach is based on [5, 4], and aims to improve the compensation of luminosity by using principal component analysis (PCA) [6].

2.1. Image enhancement on a single color plane

The main idea is that the image can be enhanced by estimating the background luminosity and contrast distribution in order to compensate for uneven illumination. Thus, the enhanced image $U(x, y)$ is expressed as:

$$U(x, y) = \frac{I(x, y) - L(x, y)}{C(x, y)},$$

where $I$ is the original image, $C$ and $L$ are the contrast and luminosity drifts, respectively. $L$ and $C$ can also be understood in terms of gain and offset. They have to be estimated by sampling the original image. The sampling approach of [4] divides the whole image into a square sampling grid, whereas in [5] they use a more intuitive sampling scheme based on the knowledge of the illumination distribution that leads to less computational burden. Therefore, we decided to use a similar type of non-uniform sampling grid shown in figure 1(b). The sampling is coarse in the central region and dense in the periphery.

As described in [5], this enhancement is oriented towards compensating the green channel of the RGB retinal image because it is the component with highest contrast. Thus, in order to estimate accurately the background luminosity the first step must be to separate the image into a set of background and foreground pixels. The foreground set consists of pixels belonging to retinal structures, such as the OD and blood vessels, while the remaining pixels are considered to belong to the background. The next step is to estimate the $C$ and $L$ components using zero mean and unit variance aims to compensate lighting variation and enhancing local contrast but also introduces artifacts [2]. Histogram matching between the red and green planes have been used as a preprocessing step for vessel segmentation [3]. 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 automatic analysis, as a preprocessing stage, they are all formulated for a single color plane or for gray-scale images.

Retinal images are acquired with a digital fundus camera, which captures the surface of the retina, pupil dilation (highly variable among patients), or presence of like micro-aneurysms. While most of the aforementioned methods are motivated by automatic enhancement method is used for equalizing uneven illumination in the intensity. Most approaches [1] are designed for gray-scale images. Attempts to extend them to color images tend to produce hue-shifting related artifacts [4], given by the introduction of new components using principal component analysis (PCA) [6].
only the background pixels. As pointed out in [5] this strategy is motivated by the fact that the retinal structures can bias the luminosity component. For instance, the OD is a naturally high luminosity zone, while the blood vessels typically exhibit low luminosity. The sampling scheme is as follows: for each sampling point on the grid we take a window of size \( w_0 \times w_0 \) large enough to include retinal structures and the background. We compute the local mean \( \mu \) and the standard deviation \( \sigma \) for each point. We perform bi-cubic interpolation to obtain \( \mu_0 \) and \( \sigma_0 \) for all \((x, y)\) points. To identify background pixels the criteria in [4] states that a pixel is considered to belong to the background if its Mahalanobis distance from \( \mu_0 \), defined as:

\[
D(x, y) = \frac{|I(x, y) - \mu(x, y)|}{\sigma(x, y)},
\]

is lower that a certain threshold \( t \), which for this work will be taken as 1. This threshold is somewhat critical, because, as pointed out before, any retinal structure that does not belong to the background, especially the OD, can bias the background components. Thus, to ensure that the OD region is not taken into account in this estimation we developed a strategy using PCA. In [6] a PCA based model was used to approximately localize the OD region in an intensity retinal image. More recently, in [7] they developed a model for retinal pigment identification using independent component analysis (ICA) on the RGB retinal image, although no experiments were carried out including the OD. The main drawback of ICA is that it does not prioritize the output components, whereas in PCA this is not an issue. Therefore, here we have used PCA on the three RGB channels to identify the OD region. The first principal component from the image in Figure 1(a) is shown in Figure 1(c). It can clearly be seen that the OD region has different properties than the surrounding retinal regions. Using the first principal component the OD region can be entirely left out from \( D(x, y) \) as as shown in Figure 2(b).

![Figure 2](image)

**Figure 2.** Background pixel classification using (a) the strategy in [5] and (b) with additional PCA analysis. Notice that the OD region has been left out in order not to bias the estimation of the luminosity component.

The following step involves repeating the sampling scheme but this time including just background pixels and with a smaller window of size \( w_1 \times w_1 \) to increase the precision in the estimation of \( \mu_1 \) and \( \sigma_1 \). Bi-cubic interpolation is carried out to obtain \( \mu_1 \) and \( \sigma_1 \) for all \((x, y)\). From [4] \( L \) and \( C \) can be approximated as \( \mu_1 \) and \( \sigma_1 \). The enhanced image is obtained by applying (1). In our experiments we set \( w_0 = 125 \) and \( w_1 = 51 \). The estimated \( C \) and \( L \) components are shown in Figure 3. To illustrate the impact on the single channel enhancement by applying (1) both images are shown in Figure 4.

### 2.2. Color remapping

After the single channel enhancement we perform the following color remapping: given a color image with color components \((r, g, b)\), the single plane enhancement is applied to the \( g \) plane
Figure 3. Estimated $L$ and $C$ components using background pixels (a-b) from Figure 2(a) and (c-d) from Figure 2(b). For the purpose of comparison (a) and (c), as well as (b) and (d) are in the same scale. Notice how the OD region has little influence on the components in (c-d).

Figure 4. Image enhancement on single channel from (a) the strategy in [5] and (b) with additional PCA analysis. In (b) the illumination in the surrounding area of the OD has not been modified significantly compared to that in (a).

and $g_{enh}$ is obtained. Next, the enhanced color image $(\hat{r}, \hat{g}, \hat{b})$ is computed on pixel basis as:

$$\hat{r} = \frac{g_{enh}}{v} \cdot r, \quad \hat{g} = \frac{g_{enh}}{v} \cdot g, \quad \hat{b} = \frac{g_{enh}}{v} \cdot b,$$

where $v$ is a scalar defined as $v = \max[r_{max}, g_{max}, b_{max}]$ to play a normalization role in the enhancement. Thus, the ratio of the original $r$, $g$, and $b$ is maintained. Figure 5(b) shows the enhanced color retinal image. Notice that it has good luminosity and different retinal structures are contrasted well against the background.

3. Optic disc segmentation by means of active contours

In this section we develop a strategy for OD boundary extraction in ocular fundus images [10]. The preprocessing stage consists in performing color mathematical morphology to remove the blood vessel regions. Subsequently, an active contours approach is used to determine the OD boundary. An active contour is an energy minimizing spline guided by external constraint forces influenced by image forces that pull it toward features such as lines and edges [8]. Mendels et al. [9] presented a technique to localize the OD based on active contours formulated on gray-level images. In this work we formulate our approach in the Lab color space to take full advantage of the color features available for the preprocessing and feature extraction stages.

The segmentation algorithm is fully automatic. We have processed 20 color 24 bit-depth RGB fundus images of size $768 \times 576$ pixels. All images were acquired using a Topcon TRC-NW6S
Figure 5. (a) Original color retinal image with uneven illumination and (b) resulting enhanced color retinal image.

retinograph and a 3CCD Sony DXC-990P camera. The accuracy of the method is compared to ground-truth manual segmentation produced by an expert. The manual segmentation was carried out by an ophthalmologist with the use of an assisted graphical user interface.

3.1. Color mathematical morphology

Active contour methods generally work by locking onto homogeneous regions of a given image. This task is made extremely difficult since the OD region is fragmented into multiple subregions by blood vessels. Furthermore, the blood vessels enter the OD from different directions with a general tendency to concentrate around the nasal side of the OD region. Mathematical morphology can extract important shape characteristics and also remove irrelevant information. It typically probes an image with a small shape or template known as a structuring element. Using gray-level morphology, the operation can be applied to the intensity or lightness channel. Osareh et al. [11] showed that in retinal images color morphology outperforms gray-level morphology, which results in more homogeneous regions and better preservation of the OD edges. They used a definition of color morphology within the CIELAB [12] color space (from now on Lab space) based on a color difference metric. We performed a closing operation, i.e. dilation to first remove the blood vessels and then an erosion to approximately restore the boundaries to their former position.

In color morphology, each pixel must be considered as a vector of color components. Definitions of maximum and minimum operations on ordered vectors are necessary to perform basic operations. Hence, for each arbitrary point \( x \) in the color space, the definitions for dilation \( (I_d) \) and erosion \( (I_e) \) by structuring element \( B \) are:

\[
I_d(x) = \{ I(y) : I(y) = \max[I(z)], z \in B_x \} \tag{4}
\]

\[
I_e(x) = \{ I(y) : I(y) = \min[I(z)], z \in B_x \}. \tag{5}
\]

A proper lexicographical order in the Lab space was introduced in [11] such that basic morphological operations could be performed. This is a problem-oriented formulation based on the knowledge that the OD region contains contrasting pixels: bright, almost saturated regions crossed by dark blood vessel regions. These color differences will reside in well-separated
regions of the Lab color space. Given that color differences in the Lab space correspond to the metric distance between them, the basic morphological operations of dilation and erosion can be defined using the color difference of all pixels within the structuring mask to a certain reference point. The color difference within the Lab color space can be obtained using the Euclidean norm, and the reference point is established at the origin \((0,0,0)\). The dilation is the furthest point from the origin, and the erosion is the point closest to the origin. The closing operation involves a dilation followed by an erosion. An example of closing using this formulation with a disc type-structuring element is shown in Figure 6. It is evident that this approach produces a more homogeneous region while approximately preserving the OD edges.

![Figure 6](image)

**Figure 6.** Color morphology closing. (a) Original ROI with optic disc inside, (b) Lab closing with a 25x25 disc-type structuring element. The result produces a homogeneous region while approximately preserving the OD edges.

### 3.2. Optic disc segmentation

The optic disc boundary is determined by fitting a geometric active contour model, namely the Chan-Vese model [8]. The active contour consists of a set of points placed near the contour of interest that are gradually brought close to the exact shape of the desired region in the image. The performance is evaluated by fitting the active contour onto the optic disc and comparing with hand-labeled ground truth. The Chan-Vese model establishes the following energy function in level-set formulation for an image \(u_0\):

\[
F(c_1, c_2, \phi) = \int_{\phi>0} |u_0(x, y) - c_1|^2 H(\phi) dxdy + \int_{\phi<0} |u_0(x, y) - c_2|^2 (1 - H(\phi)) dxdy + g(\phi),
\]

where \(\phi\) is a signed distance function that is zero exactly at the boundary \(Q\), that increases in absolute value with respect to the distance from \(Q\) and that is positive inside and negative outside. \(c_1\) and \(c_2\) represent the average intensity value of \(u_0\) inside and outside the curve, respectively. \(H(.)\) is the Heaviside function and \(g(.)\) is any function evaluated over the boundary. If we minimize \(F\) with respect to \(\phi\) and parameterizing the descent direction by an artificial time \(t > 0\) (number of iterations) we obtain:

\[
\frac{\partial \phi}{\partial t} = \delta(\phi) \left[ \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) - (u_0 - c_1)^2 - (u_0 - c_2)^2 \right],
\]

where \(\delta(.)\) is the Dirac function. By minimizing the fitting error in (6) the model looks for the best partition of \(u_0\) (see [8] for more details).
3.3. Results

The ROI is selected manually as a window of $150 \times 150$ pixels, with the whole OD inside. We applied the Lab closing to all images using a symmetrical 25-by-25 pixels disc-structuring element since the blood vessels were determined not to be wider than 20 pixels. The Lab closing allowed to remove the blood vessels cleanly and provided the required uniform OD region to initialize the active contour. The active contours approach requires an intensity or gray-scale image to perform the optimization procedure. Therefore, instead of solely using the lightness channel $L$ and, more importantly, to be consistent with the color mathematical morphology approach, we decided to use the weighting function based on the Euclidean distance within the Lab space. This feature is fundamental to obtain a uniform OD region because our approach is based on the segmentation of pixels with similar color properties.

Following the color morphological preprocessing step, we initialized the contour as a circle with the center at the brightest area and with a diameter equivalent to 80% of the ROI diameter. From these initial conditions the active contour iteratively shrank towards the final boundary. The number of iterations for the final contour convergence was determined empirically and set to 450 for all cases. In Figure 7(a)-(c) we show the hand-labeled ground-truth OD, the initial contour, and the final contour respectively.

![Figure 7](image_url)

**Figure 7.** Optic disc segmentation results. (a) hand labeled contour, (b) initial contour, (c) final contour, and (d) overlay of (a) and (c).

In Figure 7(d) we show the hand-labeled boundary together with the final contour to illustrate the close match achieved. We quantify the accuracy of the boundary localization against the manually labeled ground-truth produced by an expert. We use a simple and effective overlap measure of the match between two regions as:

$$M = \frac{n(R \cap T)}{n(R \cup T)} \times 100,$$

where $R$ and $T$ correspond to the ground-truth and the final OD contour region respectively, and $n(.)$ is the number of pixels in a region. In the optimal case, when both contours perfectly match $M = 100$. The measure $M$ represents the accuracy. When compared with the hand-labeled ground-truth information from the expert, our method was able to localize the OD pixels in all test images with an average accuracy of 85.67% ($\sigma = 7.82$). Additional tests are shown in Figure 8.

4. Summary and conclusions

In this work we have developed a strategy for retinal image enhancement and OD segmentation. We showed that the problem of non-uniform illumination and poor contrast in retinal images may be addressed via an image enhancement technique based on the knowledge of luminosity distribution in the retina. With the use of additional PCA analysis we were able to leave
out the OD region so as to estimate proper luminosity components for the illumination compensation. The resulting enhanced image showed remarkable gain in contrast related to retinal structures against the background. The background exhibited a much more uniform illumination distribution, in spite of a minor decrease in intensity.

As regards to feature extraction, we presented a strategy for optic disc segmentation by means of active contours. The preprocessing stage consisted in performing color mathematical morphology to provide a vessel-free OD region with uniform color distribution and preservation of sharp edges. The active contours algorithm yielded a fair approximation to the actual hand-labeled optic disc.

Acknowledgments
This research has been funded by the Spanish Ministerio de Ciencia e Innovacion y Fondos FEDER (project DPI2009-08879). The first author also thanks the Spanish Ministerio de Educacion for an FPU doctoral scholarship.

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Figure 8. Other OD segmentation results. Ground-truth in white and algorithm output in black. \( M \) values are: (a) 92.61, (b) 90.32, (c) 88.15.