Retinal fundus image enhancement with image decomposition and visual adaptation

Thitiphat Klinsuwan and Taiabur Rahman

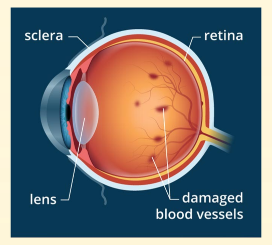
Medical Imaging and Image application, Erasmus Mundus program

Abstract

Retinal fundus photography has been widely used to diagnose various prevalent diseases because many important diseases manifest themselves on the retina. However, the quality of fundus images obtained from practical clinical environments is not always good enough for diagnosis due to uneven illumination, blurring, low contrast, etc. In this paper, we propose a simple yet efficient method for fundus image enhancement. We first conduct image decomposition to divide the input image into three layers: base, detail, and noise layers; and then illumination correction, detail enhancement and denoising are conducted respectively at these three layers. Specifically, a simple visual adaptation model is used to correct the uneven illumination at the base layer and a weighted fusion is employed to enhance details and suppress noise and artifacts. The proposed method was evaluated on public datasets (DIARETDB0 and DIARETDB1), and also on some challenging images collected by us from the hospital. In addition, quality assessments by ophthalmologists were implemented to further verify the contribution of the proposed method in helping make diagnosis. Experimental results show that the proposed method outperforms other related methods and can simultaneously handle the tasks of illumination correction, detail enhancement and noise (and artifact) suppression.

Introduction

Retinal fundus images are photographs of the back of the eye, which can be used to assess the health of the retina and detect abnormalities such as diabetic retinopathy, glaucoma, and macular degeneration. However, these images can sometimes be of poor quality due to factors such as low contrast, noise, and motion blur. Image decomposition and visual adaptation are techniques that can be used to enhance the quality of retinal fundus images and make them easier to interpret.Image decomposition involves separating the image into different components or layers, such as the background, vessels, and lesions. Each layer can then be processed separately to improve its visibility or to remove artifacts.
Visual adaptation refers to the process by which the human visual system adjusts to different lighting conditions and image content. Techniques that mimic this process, such as histogram equalization or contrast limited adaptive histogram equalization (CLAHE), can be used to improve the contrast and visibility of retinal fundus images. By using image decomposition and visual adaptation techniques, it is possible to enhance the quality of retinal fundus images and make them more useful for diagnosis and monitoring of eye diseases.



Methodology

The framework of the proposed method is shown in Fig. 1. Inspired by the mechanisms of visual adaptation and multi-pathway processing in biological vision system the proposed method first decomposes the input image into three layers, which represent respectively the base, details, and noise contained in the image. Then, the illuminant correction is implemented at the base layer. Finally, the details are boosted for contrast enhancement and combined with the corrected base map with a weighted manner to achieve flexible enhancement of different components of fundus photography, while the noise layer is discarded for denoising in a simple way.

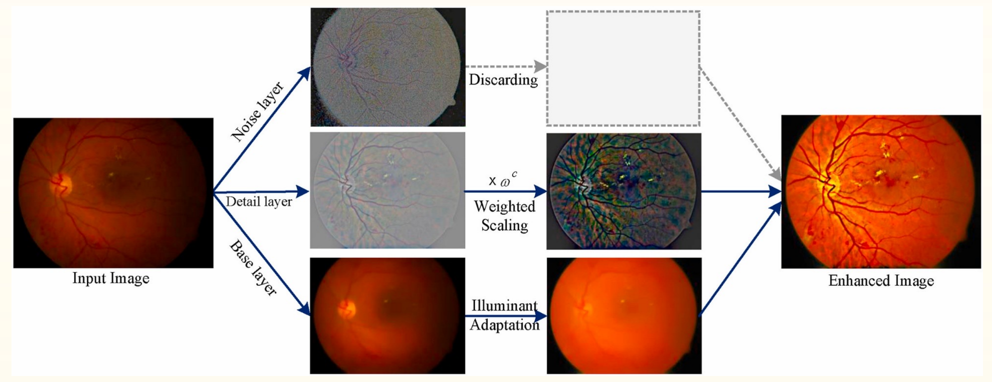


Fig. 1. The framework of the proposed fundus image enhancement method.

Image decomposition

Employed the well-known total-variation (TV) based structure-texture decomposition method1. Based on the TV regularization, the base layer can be obtained by minimizing the following objective function below. Calculate the regulation parameter(λ^c_1 ,c ∈ {R,G,B}) based on the global noise estimation[1] - in each color channel.

$$\min_{l^c_{base}} \sum_{(x,y)} \left(l^c_{base}(x-y) - l^c(x,y)\right)^2 + \lambda^c|\nabla l^c_{base}(x-y)|$$

$$\lambda^c_1 = \sqrt{\frac{\pi}{2}}\frac{1}{6(W-2)(H-2)}\sum_{(x,y)}|(I^c * N_s)(x,y)| \quad N_s = \begin{bmatrix} 1 & -2 & 1 \\ -2 & 4 & -2 \\ 1 & -2 & 1 \end{bmatrix}$$

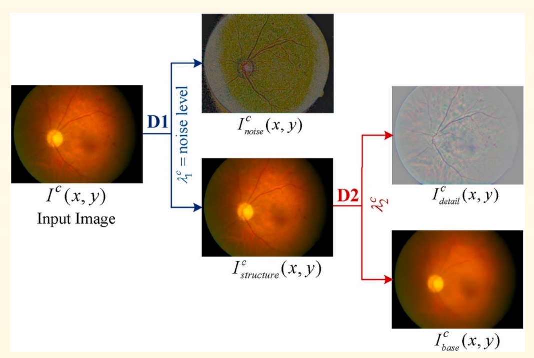


Fig. 2. The computational flow of two-step image decomposition. Note that the noise layer is scaled to clearly show the noise in the image.

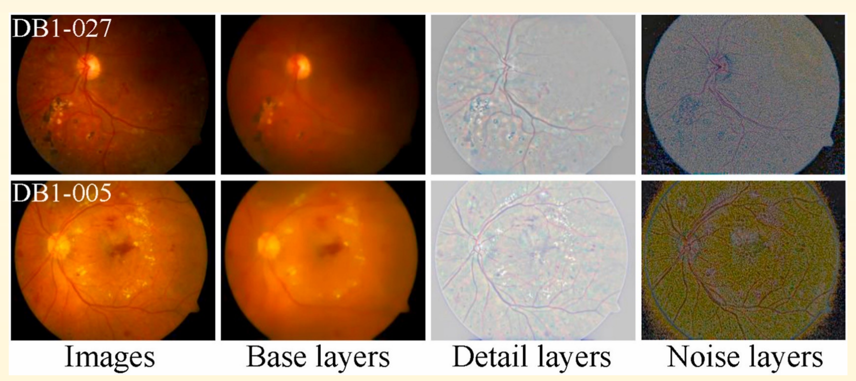


Fig. 3. Examples of image decomposition. Note that the noise layers are scaled to clearly show the noise in the images. The image numbers are labeled on the top-left corner of the original images (DB1 denotes the DIARETDB1 dataset).

Illuminant correction with visual adaptation

Adjust the uneven illuminant, the classical Naka-Rushton equation on V space of base layers. To simplify the method, authors set a fixed value as n = 1.0. M_g denoting the mean. S_g denoting the standard deviation.

$$L_{out}(x,y) = \frac{L_{in}(x,y)^n}{L_{in}(x,y)^n + \sigma_g^n} \qquad \sigma_g = \frac{M_g}{1 + exp(S_b)}$$

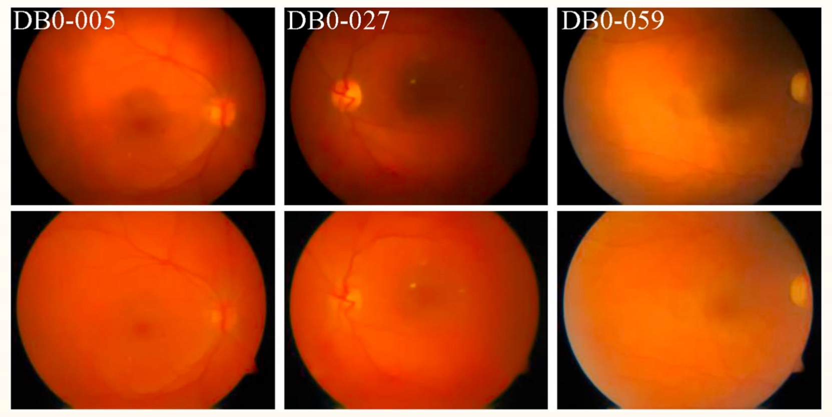


Fig. 4. Examples on three images illustrating the uneven illuminant correction with the proposed visual adaptation model (at the base layer). Top: the base layers of the given images; Bottom: the corrected base images with visual adaptation. The image numbers are labeled on the top-left corner of the original images (DB0 denotes the DIARETDB0 dataset).

Fusion with denoising, artifact suppression, and detail enhancement

In order to flexibly enhance the details, authors will set different scaling factors for different channels with the specific enhancement goal for retinal fundus images.

-to remove noise, we simply discard the noise layer decomposed.
-the final enhanced map can be obtained by fusing the enhanced base layer and the highlighted detail layer in a weighting way

f(x,y) represents a Gaussian filter (with the standard deviation as 10) * denotes the convolution operator set $\alpha_R = \alpha_G = 600 \ and \ \alpha_B = 0$ for general fundus image enhancement)

$$I^c_{out} = I^c_{enh}(x,y) + \omega^c(x,y) \cdot I^c_{detail}(x,y);$$
$$\omega^c(x,y) = \alpha^c \cdot (|I^c_{detail}(x,y)| * f)(x,y)$$

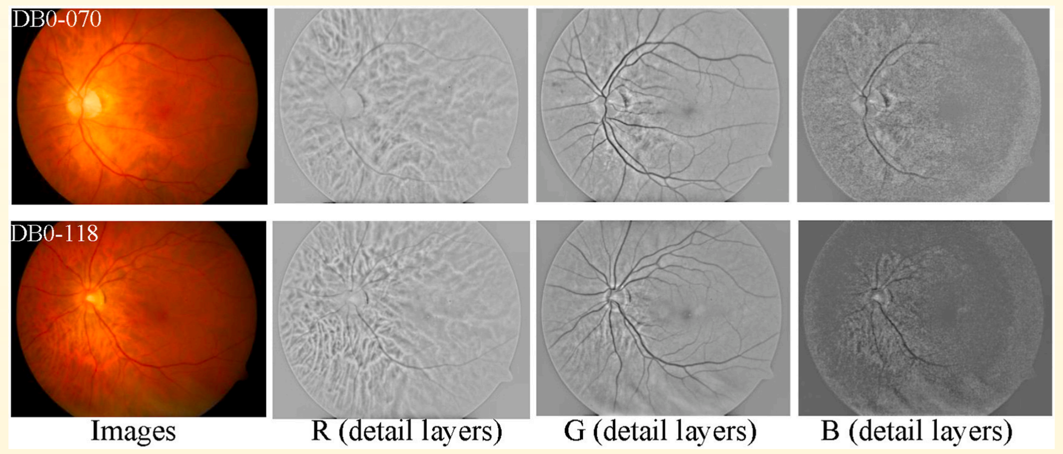


Fig. 5. Examples of three channels (*R*, *G*, and *B*) of fundus photography. *R* channel main contains the veins on the surface of the inner retina, while vessels on retina are mainly present in *G* channel.

Results

To evaluate the performance of the proposed method, we tested it on two widely used public datasets: diabetic retinopathy database DIARETDB0 (130 images) and DIARETDB1 (89 images), which contain images with a size of 1500×1152 pixels (downloaded from http://www.it.lut.fi/project/imageret/). In addition, we also evaluated the proposed method on 50 challenging images (with the size of 1011×971 pixels) collected from the West China Hospital of Sichuan University, China, which mainly suffer from serious blurring.

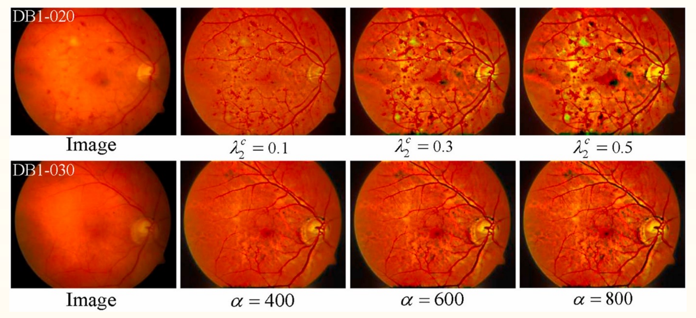


Fig. 6. The effect of the main parameters on the final results. The top row: various λ_2^c with fixed α=600; The bottom row: various α with fixed λ_2^c=0.3.

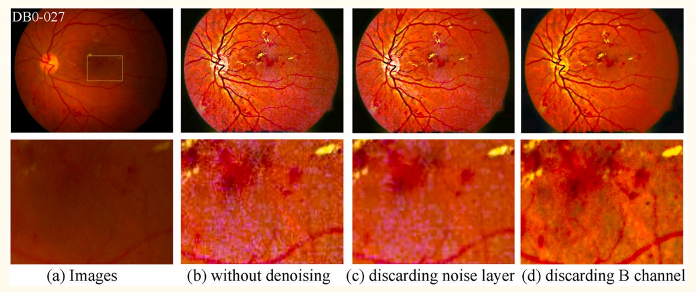


Fig. 7. Illustration of selectively enhancing different components with various scaling factor α_c for the original image (top row) and the zoomed-in patch.

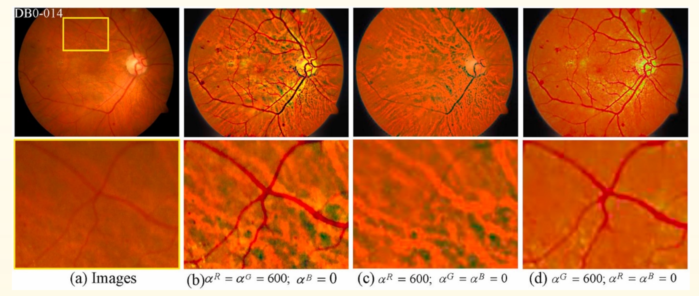


Fig. 8. Illustration of the noise and artifact suppression operation for the original image (top row) and the zoomed-in patch.

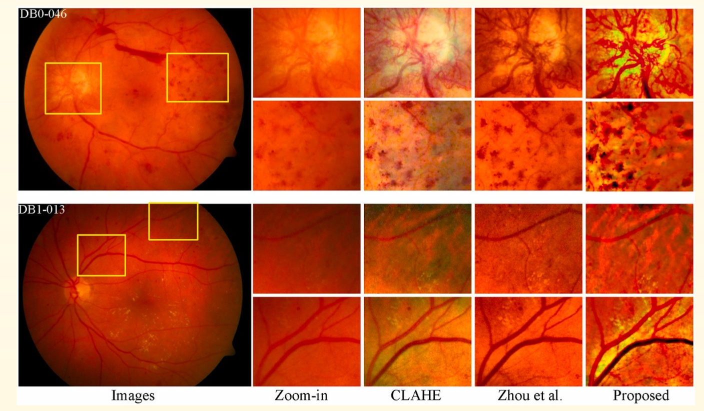


Fig. 9. Zoomed-in view of two test images. The image in the top row is from DIARETDB0 and the image in the bottom row is from DIARETDB1.

Conclusion

simple flowchart for general retinal fundus image enhancement to simultaneously realize the illumination correction, detail enhancement, and noise (and artifact) suppression.

The experimental results with qualitative and quantitative comparisons demonstrate that the proposed method can adjust uneven illuminant with a visual adaptation mechanism and achieve clear noise suppression and detail enhancement.

Actually, this work has a quantitative comparison. However, they compare only contrast enhancement and subjective evaluation from ophthalmologists.