Retinal fundus image enhancement with image decomposition

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***Abstract* - Retinal fundus photography serves as a vital tool in diagnosing prevalent diseases due to their manifestation on the retina. However, practical clinical environments often yield fundus images of suboptimal quality for accurate diagnosis, characterized by uneven illumination, blurring, and low contrast. This project introduces a straightforward yet effective method for enhancing fundus images. The approach involves image decomposition, segregating the input image into three layers - base, detail, and noise. Subsequently, illumination correction, detail enhancement, and denoising are applied to these respective layers. The correction of uneven illumination at the base layer utilizes a simple visual adaptation model, while a weighted fusion is employed for detail enhancement and noise suppression.**

Keywords: Retinal fundus photography, Image decomposition, Denoising, Blurring, Detail enhancement, TV-Method, Gaussian filter.

INTRODUCTION

Retinal fundus photography serves as a non-invasive and cost-effective means for directly observing circulatory conditions, crucial in diagnosing prevalent eye and cardiovascular diseases. Despite its widespread use, the clinical utility of retinal images is often compromised by factors such as non-uniform illumination, low contrast, and imperfections like unexpected eye movement. Traditional histogram-based methods, such as histogram equalization (HE) and contrast limited adaptive histogram equalization (CLAHE), fall short in simultaneously enhancing illumination and contrast. In contrast, this report introduces an innovative fundus image enhancement framework. The main contributions of this work can be summarized as follows: (i) we propose a global noise estimation based image decomposition method to divide the input image into three layers, i.e., the base, detail, and noise layers. (ii) The enhanced image is achieved by the weighted addition of all the layers using a Gaussian filter with standard deviation 10. This enables efficient adjustment of uneven illuminant at the base layer and detailed enhancement at the detail layer, resulting in superior performance in illuminant correction, detail enhancement, and noise/artifact suppression compared to existing methods.

DATASET

The drive dataset is a publicly available collection designed for retinal vessel segmentation tasks. It consists of two main folders: 'training' and 'test.' The dataset is utilized for developing and evaluating algorithms related to retinal vessel segmentation. The DRIVE dataset can be downloaded from the following link: Drive Dataset.

METHODS

The proposed method's framework, illustrated in Fig. 1, draws inspiration from biological vision systems, incorporating visual adaptation and multi-pathway processing mechanisms. Initially, the input image undergoes a three-layer decomposition, segregating the base, details, and noise components. Subsequently, illuminant correction is applied to the base layer. The details are then intensified for contrast enhancement and tactically merged with the corrected base map, employing a weighted approach for versatile enhancement of diverse fundus photography elements. Meanwhile, a straightforward denoising approach involves discarding the noise layer. This method leverages biological vision concepts to efficiently enhance fundus images by addressing illumination, contrast, and noise intricacies.

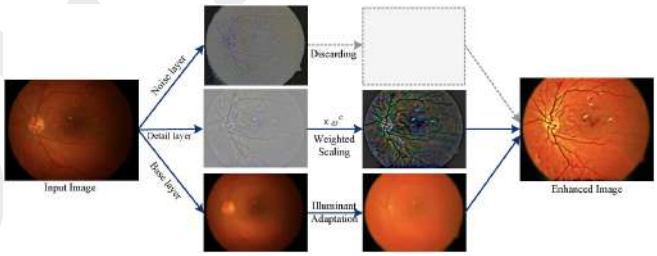


Fig. 1. The framework of the proposed fundus image enhancement method. [1]

IMAGE DECOMPOSITION

In order to separate the input image into various frequency channels, we employed the well-known total-variation (TV) based structure texture decomposition method. In their method, the input image is considered as the superimposition of the base and detail layers, i.e.,

$$I^c(x,y) = I^c_{base}(x,y) + I^c_{detail}(x,y), c \in \{R,G,B\} \quad \text{- (1)}$$

Based on the TV regularization, the base layer can be obtained by minimizing the following objective function

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

where λ^c, $c \in \{R, G, B\}$ is the regulation parameter which controls the degree of details in the texture.
Therefore, we decompose the input image into three layers, i.e., the base, detail and noise layers, with two steps of

decomposition. Specifically, the input image can be considered as the superimposition of the structure and noise layers, while the structure layer can be further decomposed into the base layer and the detail layer. This can be described as :

$$I^c(x,y) = I^c_{structure}(x,y) + I^c_{noise}(x,y) \\ = I^c_{base}(x,y) + I^c_{detail}(x,y) + I^c_{noise}(x,y) \quad \text{-(3)}$$

In the first step we extract I^R, I^G, I^B from the original image I^c.(See Fig below)

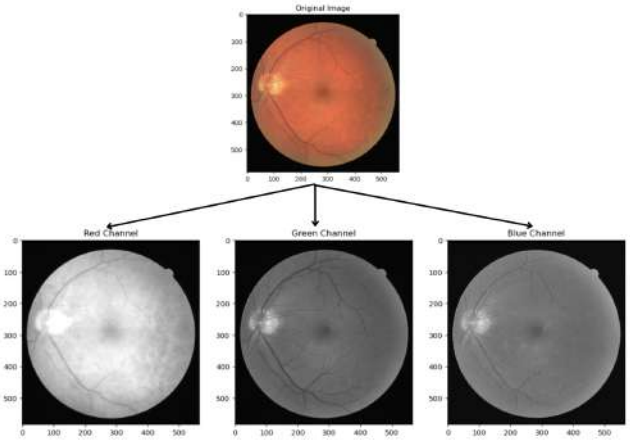


Fig. 2. Decompose original image into red, green and blue channels.

In the next step of decomposition, in order to separate the noise from the structure layer ($I_c structure(x, y)$), we calculate the regulation parameter (λ^c_1, $c \in \{R, G, B\}$) based on the global noise estimation in each color channel, i.e.,

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

$$N_s = \begin{bmatrix} 1 & -2 & 1 \\ -2 & 4 & -2 \\ 1 & -2 & 1 \end{bmatrix} \quad (5)$$

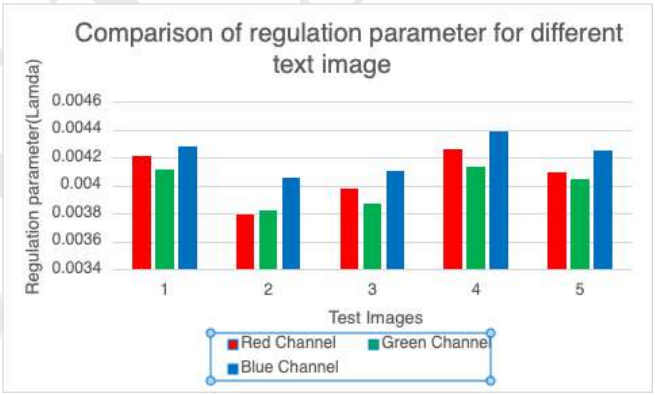
where $*$ denotes the convolution operator, and $c \in \{R,G,B\}$. W and H are the width and height (in pixel) of the image ($I_c(x,y)$), respectively. Thus, this decomposition can divide the input image into the structure layer and the noise layer ($I_c noise(x, y)$) (See Fig. 3.)

The the regulation parameter value for 'test image 12' was $\lambda^R_1 = 0.004269$, $\lambda^G_1 = 0.004137$, $\lambda^B_1 = 0.004388$.

For different test images value of regulation parameters are mentioned in the table below.

Test image no.	Red Channel	Green Channel	Blue Channel
01_test.tif	0.00420869458556960	0.00411562520285811	0.00427684413356346
04_test.tif	0.00379459733209557	0.00382670211915853	0.00405710559099310
08_test.tif	0.00397459113827538	0.00386964683432505	0.00410041030377188
12_test.tif	0.00426416421766379	0.00413704006082273	0.00438811839552995
16_test.tif	0.00409815281874479	0.00404425317623755	0.00425086680585971

A graph representation of all the values is also shown below for all channels for 5 test images.(See Below)



In the next decomposition step of the proposed method, the structure layer ($I_c structure(x, y)$) undergoes further subdivision into the base layer ($I_c base(x, y)$) and the detail layer ($I_c detail(x, y)$), employing a regulation parameter (λ^c_2 $c \in \{R, G, B\}$), typically set at $\lambda^c_2 = 0.3$.(See Fig. 3.) illustrates three examples of this image decomposition, revealing that the base layer primarily captures illuminant distribution, while crucial details such as vascular structures, the optic disc, and visible lesions are concentrated in the detail layer.

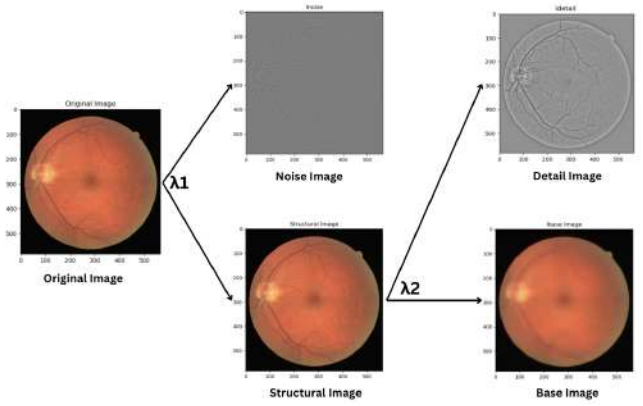


Fig. 3. The computational flow of two-step image decomposition.

Interestingly, the noise layer appears less informative for disease diagnosis, and although structured vessels are present in this layer, they are well preserved in the structure layer. Consequently, discarding the noise layer does not significantly compromise details, as they are meticulously enhanced in the detail layer.(See Fig. 4)

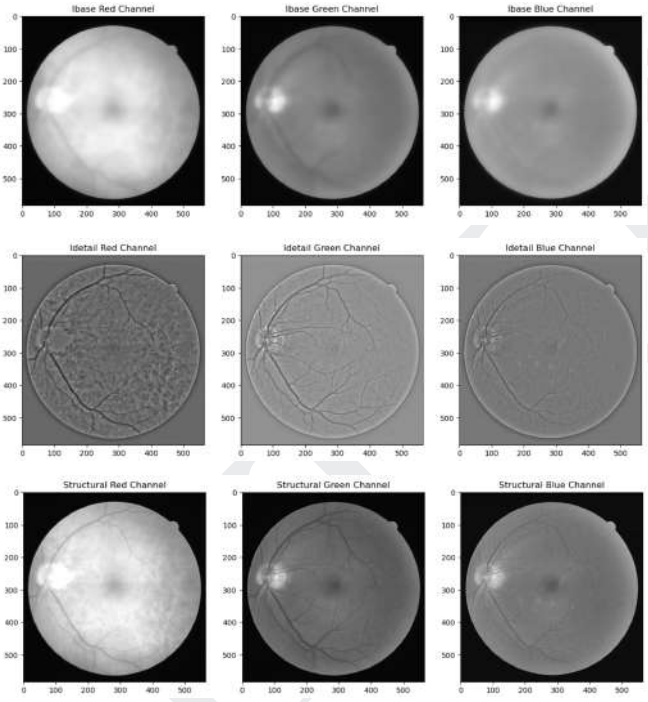


Fig. 4. Examples of image decomposition. (Ibase, Idetail, Istructual for R, G and B channels)

FUSION WITH DENOISING, ARTIFACT SUPPRESSION AND DETAIL ENHANCEMENT

In retinal fundus photography, each color channel serves a distinct purpose, with the R channel capturing veins due to its darker red presentation, while arteries are predominantly visible in the G channel, often chosen for vessel and lesion extraction methods due to its heightened contrast. The B channel is considered an artifact, contributing little valuable information.To enhance details flexibly, different scaling factors are assigned to each channel. Noise removal involves straightforwardly discarding the noise layer, as demonstrated in Fig. 3, where it contains minimal information relevant to disease diagnosis, primarily comprising electronic noise from the imaging process. This strategy allows for specific enhancement goals tailored to retinal fundus images.

In order to remove noise, we simply discard the noise layer decomposed., since as illustrated in Fig. 4, almost no useful information for disease diagnosis is contained in the noise layer, which mainly contains electronic noise from the imaging process. Based on the considerations analyzed above, the final enhanced map can be obtained by fusing the enhanced base layer and the highlighted detail layer in a weighting way, i.e.,

$$I^c_{out} = I^c_{enh}(x,y) + \omega^c(x,y) \cdot I^c_{detail}(x,y) \quad \text{-(6)}$$

where $\omega^c(x,y)$, $c \in \{R, G, B\}$ indicate the spatially-dependent weightings of different channels, which are defined by considering the local magnitude of the detail layer, i.e.,

$$\omega^c(x,y) = \alpha^c \cdot \left(\left| I^c_{detail}(x,y) \right| * f \right)(x,y) \quad \text{-(7)}$$

where $f(x, y)$ represents a Gaussian filter (with the standard deviation as 10) and $*$ denotes the convolution operator, and we set $\alpha^R = \alpha^G = 600$ and $\alpha^B = 0$ for general fundus image enhancement. ω^c_1 and ω^c_2 are considered 0 and 1 in all three cases.

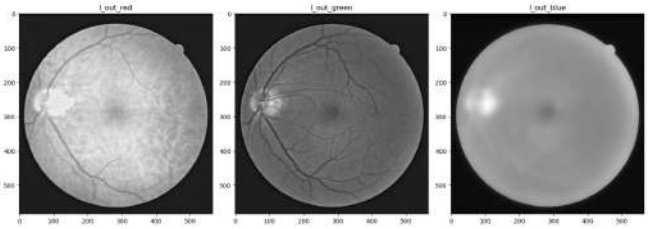


Fig. 5. Enhanced Images in red, green and blue channel

Merge all three channels to get a final enhanced image containing most of the informations (See Fig. 6)

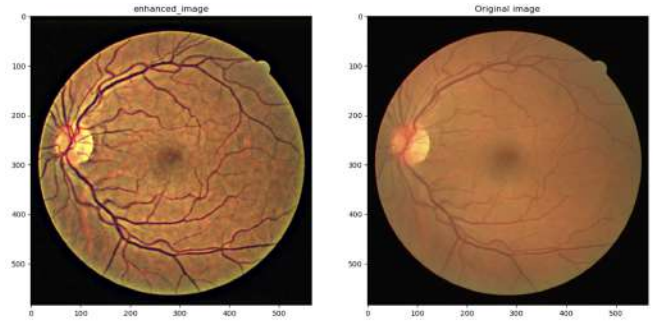


Fig. 6. Enhanced Image and Original Image(test image 12)

This means that we selectively enhance the details contained in the *R* and *G* channels because they represent mainly the useful information (especially the veins and arteries), whereas suppress the information contained in the *B* channel. In the following experiments, we will demonstrate how to flexibly enhance different components by adjusting the scaling factor (α^c, $c \in \{R, G, B\}$) of each channel.

QUANTITATIVE COMPARISON

Image contrast is an important aspect which reflects the visible details after enhancement. In order to quantitatively evaluate the performance of contrast enhancement, we employed a quantitative measure of image contrast enhancement based on the local contrast index, which has been widely used in related works . Firstly, the local contrast index (*Clocal*) is defined as

$$C_{local} = \frac{max - min}{max + min} \quad \text{- (8)}$$

where *max* and *min* represent respectively the maximum and minimum intensity values within a $N \times N$ window. We set $N = 50$ following the previous work. Then, the contrast enhancement measure (Δ*local*) is defined as the average difference of *Clocal* between the original image and the enhanced image (i.e., the average *Clocal* of the enhanced image minus the average *Clocal* of the original image). Note that we computed Δ*local* only based on the effective pixels in the retina region, i.e., excluding the background pixels outside the retina in the images.. In order to conveniently compare with the considered methods, we first computed the contrast enhancement measure in the *R*, *G* and *B* channels, respectively. (Δ*local*) values for two test images are shown in the given table and it can be seen that the values are positive signifying that the results have better improvement . (See table below)

Test image no.	(Δ*local*) Red Channel	(Δ*local*) Green Channel	(Δ*local*) Blue Channel	(Δ*local*) combine (RGB)
01_test.tif	0.06287797	0.24488354	0.24488354	0.15964876
04_test.tif	0.06145648	0.22659893	0.23554868	0.29575628
08_test.tif	0.07895882	0.06864411	0.21139015	0.17151722
12_test.tif	0.10890817	0.06474 9435	0.21041998	0.19307664
16_test.tif	0.08612 5664	0.05101 6062	0.22434 3	0.15892933

Enhanced image for the above test images are shown in the given below

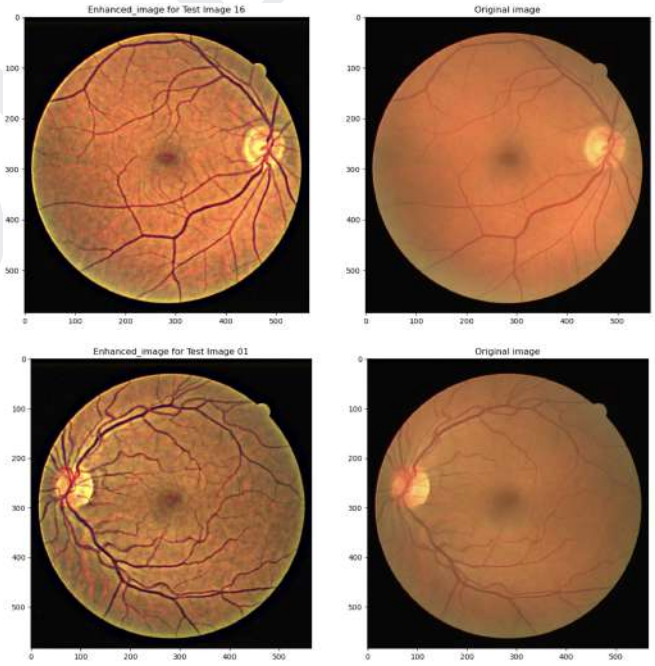


Fig. 9. Enhanced Image vs Original Image for 5 datasets

CONCLUSION

The Report introduces a flowchart for enhancing retinal fundus images, addressing issues of uneven illumination, detail enhancement, and noise suppression simultaneously. The proposed method demonstrates effective adjustment of uneven illuminant using a visual adaptation mechanism, leading to clear noise suppression and enhanced details. The results, evaluated qualitatively and quantitatively, illustrate the method's ability to selectively enhance different components in fundus images. Overall, the proposed enhancement method proves valuable for specific clinical diagnoses, emphasizing its potential in assisting medical professionals in conditions such as diabetic retinopathy.

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