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ORIGINAL ARTICLE

A complexity reduction based retinex model for low luminance retinal fundus image enhancement

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Abstract
Retinal fundus images play significant roles in the early detection and treatment of various ocular diseases. However, they are often suffered from low luminance in the process of shooting. To address this problem, we propose a Complexity Reduction Retinex (CR^2) model for the enhancement of low luminance retinal fundus images. The proposed method enables the divided illumination component to be spatially smooth and the reflectance component to be piece-wise continuous. Meanwhile, to improve the computational efficiency, we divide the illumination and reflection components into two independent sub-problems and solve them efficiently by Alternating Direction Minimizing (ADM) method. Comparative results demonstrate that the proposed method outperforms the state-of-the-art methods in terms of qualitative and quantitative evaluations.

Keywords Medical image process · Retinal fundus image enhancement · Retinex decomposition · Alternating direction minimizing

1 Introduction

Medical imaging analysis plays the significant auxiliary role in the diagnosis of diseases and the formulation of treatment plans. Especially for human retinal images, it has the potential to reveal important information about the retina, ophthalmology, and even systemic diseases such as diabetes, hypertension, and arteriosclerosis. However, there are degradations in the captured medical images (Wu et al. 2016; Jeon et al. 2010), e.g., uneven and low brightness, which affect the diagnosis results and even lead to misdiagnosis. Therefore, high-quality retinal fundus images are essential for the timely detection and treatment of eye diseases (Lai et al. 2021). To this aim, the demand for an effective yet robust model for retinal fundus image luminance-level enhancement is highly urgent.

The low luminance enhancement of retinal fundus images is a significant branch of low-light image enhancement. There are various methods to deal with low-light image enhancement problem, and they can be commonly classified as histogram equalization (HE) based methods (Ibrahim and Kong 2007), Retinex based methods (Lee et al. 2013), and learning based methods (Lore et al. 2017). The HE based methods enhance the visibility of low-light images by flattening the histogram via stretching the corresponding dynamic range of the intensity (Singh and Dixit 2015). HE based methods can be further classified into global and local methods. Although these methods are effective for dynamic range enhancement, the enhanced image often exhibits unnatural details. The Retinex based methods enhance low-light images by image decomposition. These methods decompose an image into two separate components, namely, reflectance and illumination. Then, the two decomposed components are further processed to obtain the enhanced results. The single-scaled Retinex (SSR) (Jobson et al. 1997a) method and multi-scaled Retinex (MSR) (Jobson et al. 1997b) method are the pioneering works in this field. However, the estimation of the illumination and reflectance components from the observed image is inherently an ill-posed problem. In order to make this problem tractable, some attempts are to transform the illumination or reflectance decomposition into a statistical reasoning problem. By proposing different priors for illumination and reflectance and defining variational optimization, these methods seek the optimal solutions (Fu et al. 2015). The deep learning

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based methods model the feature maps from the high visual quality images to enhance the low-light images. Although the deep learning based approaches have achieved remarkable achievements, the enormous computational burden in practical application and the complex structure of the model limit their practical application.

In this paper, we aim to build an effective Retinex model combined with two constrains to make illumination map piece-wise smooth and reflectance component piece-wise continuous. The proposed method considers the whole update problem as two separate problems which are computed independently. To reduce the computation cost and improve accuracy, an Alternating Direction Minimizing (ADM) based method is presented to solve the complexity problem efficiently. Experiments on public datasets are conducted to prove the superiority of our method in low luminance retinal fundus image enhancement compared with other state-of-the-art methods.

The organization of this paper is as follows: In Sect. 2, the methods of low-light image enhancement are briefly reviewed. In Sect. 3, the proposed approach is described in detail. Experimental results are demonstrated in Sect. 4. The work is concluded in Sect. 5.

2 Related work

The methods for retinal fundus image luminance-level enhancement can refer to the methods of low-light image enhancement which are divided into three categories, namely histogram equalization (HE) based method, deep learning based method and Retinex based method.

2.1 Histogram equalization based method

The HE based methods enhance the image by stretching the dynamic range of the image according to its histogram (Pizer 1990). These methods may result in unsatisfactory local illumination and amplifying potentially strong noise. BBHE (Kim 1997) uses independent histogram equalization for two sub-images obtained by mean decomposition of the input image, and constrain the obtained equalized sub-images. Zuiderveld (1994) proposed a Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm, which can alleviates the block effect effectively and suppress the noise introduced in the process of enhancement. The BPDHE (Ibrahim and Kong 2007) algorithm smooth the histogram of the input image by single-dimensional Gaussian filter, and then segments the result histogram before the process of histogram equalization. Generally, the HE based methods are not pliable enough to adjust the visual attributes in the local areas, resulting in unsatisfactory local appearances.

2.2 Deep learning based method

With the in-depth development of deep learning (Li et al. 2019), the performance of low-light image enhancement has been significantly improved. Lore *et al.* put forward the first supervised low light level enhancement method, named LLNet (Lore et al. 2017) to illuminate the image with minimum pixel saturation. LLCNN (Tao et al. 2017) utilizes a specially designed convolution module to enhance the image via using multiscale feature map. Wei et al. (2018) proposed the Retinex-Net by assuming the consistency of reflectance components between normal lighting and low-light images and the illumination component is brightened, and the reflectance component is denoised. Built by Zhang et al. (2019), the Kindling the Darkness (KinD) network connects the characteristic level of illumination and reflectance in the decomposition step. The KinD is trained by the LOL dataset (Wei et al. 2018) with paired images. Zero-DCE (Guo et al. 2020) trains a zero reference curve estimation network to estimate pixel-wise and high-order curves to dynamically adjust the range of input low-light images. Yang et al. (2020) presents a recursive band network and uses semi-supervised strategy for training. Jiang et al. (2021a) proposed an Enlighten-GAN to get rid of the construction of pairwise datasets. There is no doubt that methods based on deep learning can play excellent performance in low-light image enhancement, and these methods gradually occupy the mainstream in this domain. However, it is limited by many factors, such as the difficulty of acquiring high quality training data sets and the sharp increase of time cost and computation burden caused by model complexity.

2.3 Retinex based method

Established by Land and McCann (Land 1977), Retinex theory can be viewed as a fundamental theory that models the human eye's perception and color characteristic. The goal of the theory is to determine the reflectance property of the image by separating the effect of illumination. Pioneering works on Retinex, such as single-scaled Retinex (SSR) (Jobson et al. 1997a) method and multi-scaled Retinex (MSR) (Jobson et al. 1997b) method consider the adjusted reflectance component as the final result, usually make the enhanced images over-enhanced and non-aesthetic. Sequentially, various enhancement methods based on the Retinex have been proposed (Ren et al. 2020; Guo et al. 2017; Gu et al. 2020). Kimmel et al. (2004) proposed a variational framework Retinex algorithm based on transcendental assumptions. Based on this framework, the ill-posed problem of illumination and reflectance component estimation is transformed into an optimal quadratic programming problem. Using two specially tailored bilateral filters, Elad (2005) proposed a non-iterative Retinex algorithm to better process the edge information in the illumination component. Wang et al. (2013) proposed a bright-pass filter that combines the neighbor brightness information to preserve the natural brightness of the image. Proposed by Fu et al. (2016), the MF fuses the multiple derivatives of the initial illumination map to adjust the illumination. The Retinex based methods have obvious benefits, and they are easy to implement. These methods have prominent superiority in enhancing the contrast and brightness of images, as well as image color enhancement.

3 Methodology

3.1 Retinex theory

The traditional Retinex model elaborates the composition of low light image as,

$$O = L \odot R, \tag{1}$$

where the symbol $\odot$ means the element-wise multiply and O is the observed image. The reflectance component R describes the intrinsic properties of the object in the scene, which should be consistent under diverse brightness conditions. And the illumination component L represents the various illumination corresponding to the object. The Retinex decomposition is often performed in HSV space, as the HSV space is in line with human visual perception (Jiang et al. 2021b; Zhang et al. 2020). Furthermore, the V channel is naturally considered as the initial illumination component for Retinex decomposition. The final result is generated by converting the enhanced result from HSV space to RGB space.

Some approaches use the term of $\|O - L \odot R\|_F^2$ to estimate the components R and L simultaneously. Specifically, one component is updated by considering the previous value of the other component as a constant. However, some degradations are often observed during the process, which lead to some error amplification. Besides, this kind of alternatively updated method is often suffered from complexity and computation burden. To improve the computational efficiency, we consider the whole update problem as two separate problems, and solve them efficiently by Alternating Direction Minimizing (ADM) method. The overall architecture of the proposed model is shown in Fig. 1.

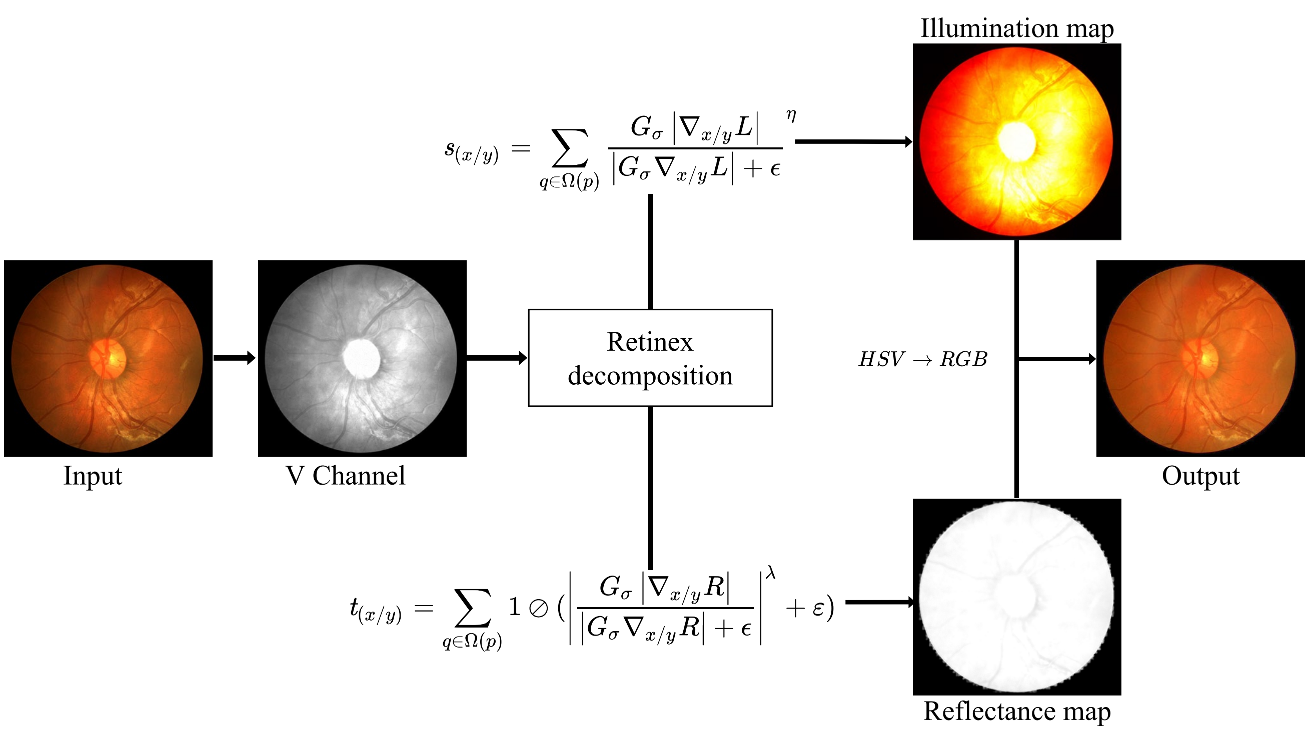

Fig. 1 The framework of the proposed model. Given the input low-light RGB image, it is first converted into HSV space. The V channel is normalized and decomposed into illumination and reflectance components. Then, these two components are estimated with the structure and texture constraints, respectively. The estimated illumination and reflectance components are integrated and the HSV space is transformed to the RGB space to generate the final result

3.2 Illumination map estimation

The proposed sub-model for illumination component estimation is formulated as

$$\underset{L}{\operatorname{argmin}} \left\| L - \hat{L} \right\|_F^2 + \alpha (s_x \| \nabla_x L \|_F^2 + s_y \left\| \nabla_y L \right\|_F^2), \tag{2}$$

where $\left\| L - \hat{L} \right\|_F^2$ constrains the fidelity between the initial illumination map $\hat{L}$ and the estimated illumination map L. The $s_x \| \nabla_x L \|_F^2$ and $s_y \left\| \nabla_y L \right\|_F^2$ can make the illumination map piece-wise smooth and preserve major structure. The symbol ∇ means the first-order partial derivative. α is the regularization coefficient.

Inspired by the work of Xu et al. (2012), the weight matrix is formulated as

$$s_{(x/y)} \leftarrow \sum_{q \in \Omega(p)} \frac{G_\sigma \left| \nabla_{x/y} L \right|}{\left| G_\sigma \nabla_{x/y} L \right| + \epsilon}^{\eta} \tag{3}$$

where G_σ is a Gaussian kernel with window size $\sigma = 3$, and x/y means the weight matrix in the x-direction (horizontal) or the y-direction (vertical). The parameter ϵ is the constant to avoid the zero denominator and η controls the smooth degree of the illumination map. The pixel q belongs to the region $\Omega(p)$ around the certain pixel p. Then, the relative total variation weight of each individual pixel is calculated. The objects of this operation are all pixels in the image, and the weights of the pixels constitute the structure information map of the image.

The augmented Lagrangian formation of (2) can be written as the follows,

$$\begin{aligned} \mathfrak{L}(L, B, Z) =& \| L - \hat{L} \|_F^2 + \alpha (s_x \| \nabla_x B \|_F^2 + s_y \left\| \nabla_y B \right\|_F^2) \\ &+ Z(B - L) + \frac{\mu}{2} \| B - L \|_F^2, \text{ s.t. } B = L \end{aligned} \tag{4}$$

where μ is the positive penalty scalar and Z is the Lagrangian multiplier. The proposed optimization method based on the framework of Augmented Lagrangian Multiplier with Alternating Direction Minimizing (ALM-ADM). The ADM algorithm is commonly used to solve the convex problem (Lin et al. 2011; Hong and Luo 2017) such as Eq.(2). The solver updates one variable at a time by modifying other variables, and each step of the updating results in a closed-form solution. We provide the solution to each sub-problem of various variables.

1)Solution to L problem: The terms related to L in Eq.(4) are selected and formulated as

$$\underset{L}{\operatorname{argmin}} \| L - \hat{L} \|_F^2 + Z(B - L) + \frac{\mu}{2} \| B - L \|_F^2. \tag{5}$$

Then, differentiate the respect to L in Eq. (5) and set the derivative result to 0, the estimated L of $(k+1)$-th iteration can be expressed as

$$L_{k+1} = \frac{\mu B_k + Z_k + 2\hat{L}}{(2 + \mu) I}, \tag{6}$$

where I is an identity matrix. Specifically, the initial illumination component L_0 is set as the V channel.

2)Solution to B problem: The terms related to B in Eq.(4) are collected and formulated as

$$\begin{aligned} &\underset{B}{\operatorname{argmin}}\ \alpha (s_x \| \nabla_x B \|_F^2 + s_y \left\| \nabla_y B \right\|_F^2) + Z(B - L) \\ &+ \frac{\mu}{2} \| B - L \|_F^2. \end{aligned} \tag{7}$$

Then, differentiate the respect to B in Eq. (7) and set the derivative result to 0, the estimated B of $(k+1)$-th iteration can be expressed as

$$B_{k+1} = \frac{\mu L_{k+1} - Z_k}{2\alpha (D_x^T s_x D_x + D_y^T s_y D_y) + \mu I}, \tag{8}$$

where D_x and D_y are the Toeplitz matrices in horizontal and vertical directions.

3)Updating Z and μ: The iteration problem of Z and μ can be solved via

$$\begin{aligned} Z_{k+1} &\leftarrow Z_k + \mu_k (B_{k+1} - L_{k+1}), \\ \mu_{k+1} &\leftarrow \mu_k \rho, \rho > 1, \end{aligned} \tag{9}$$

where ρ is the step size, which is used to update the penalty parameter.

3.3 Reflectance map estimation

Once the estimated illumination map is obtained, the term of $\| O - L \odot R \|_F^2$ is used to constrain the fidelity between the observed image O and the reconstructed image $L \odot R$. The formation of reflectance map estimation can be written as

$$\begin{aligned} &\underset{R}{\operatorname{argmin}} \| O - L \odot R \|_F^2 \\ &+ \beta (t_x \| \nabla_x R \|_F^2 + t_y \left\| \nabla_y R \right\|_F^2), \end{aligned} \tag{10}$$

where $t_{(x/y)} \leftarrow \sum_{q \in \Omega(p)} 1 \oslash \left(\left| \frac{G_\sigma | \nabla_{x/y} R |}{| G_\sigma \nabla_{x/y} R | + \epsilon} \right|^\lambda + \varepsilon \right)$. ε is a constant to avoid zero denominator (ε is set as 0.0001 in this work). λ is a positive parameter to control the sharpness degree of the reflectance map. β is the regularization coefficient. And the $t_x \| \nabla_x R \|_F^2$ and $t_y \left\| \nabla_y R \right\|_F^2$ are the regularization terms to enable the reflectance map piece-wise continuous. The solution to Eq. (10) is

$$R = \frac{L^T O}{\beta \sum_{d\in\{x,y\}} D_d^T t_d D_d + L^T L}. \tag{11}$$

3.4 Illumination adjustment

After obtaining the estimted components of the illumination L and the reflectance R, the goal is to adjust L to improve the visibility and brightness of the input image. To this aim, we adopt the Gamma correction (Pang et al. 2017; Wu et al. 2020) to adjust the illumination component. The corrected illumination is written as

$$\hat{L} = L^{\frac{1}{\gamma}}. \tag{12}$$

The enhanced result $\hat{O}$ is generated by

$$\hat{O} = R \odot L^{\frac{1}{\gamma}}, \tag{13}$$

where $\gamma = 2.2$ is an empirical value (Gu et al. 2020; Gao et al. 2018). Finally, the enhanced image is generated by reversing the space from HSV to RGB.

4 Experiments and discussion

4.1 Experimental Settings

All experiments are carried out on MATLAB R2019b with 32G RAM and Intel Core i7-9700K CPU @3.60GHz. The parameters α, β, η, and λ, are set as 0.01, 0.5, 1.25 and 2.5, respectively. The step size ρ in Eq. (9) is set as 1.5 in this work. For retinal fundus image enhancement effectiveness evaluation, we verify the proposed method on the CHASE_BD1 dataset (Zhang et al. 2016) which contains 28 color retinal fundus images (999×960), and a selected 40 samples (4288×2848) from IDRiD dataset (Porwal et al. 2018).

4.2 Qualitative evaluation

To assess the enhancement result of the proposed model, we carry out comparative comparisons with six state-of-the-art (SOTA) methods, i.e., HE (González and Woods 1981), SSR (Jobson et al. 1997a), CVC (Çelik and Tjahjadi 2011), MSRCR (Rahman et al. 2004), Dong et al. (2011), and LIME (Guo et al. 2017). Figures 2, 3, 4, 5 show the comparative results among various methods. It can be noticed from the comparative results that, although some SOTA methods can brighten the low-light retinal fundus image, there are also still some unsatisfactory degradations, *e.g.*, color distortion

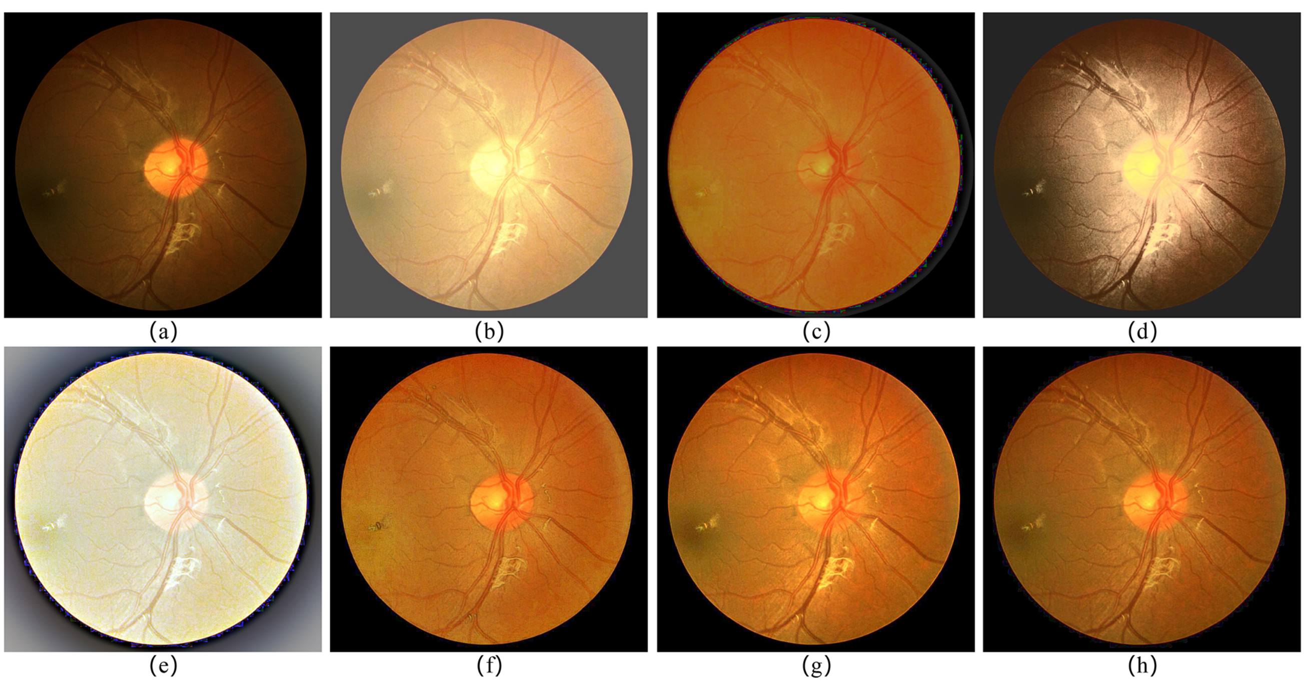

Fig. 2 Visual evaluation of an exemplar in CHASE_BD1 (Zhang et al. 2016) dataset with the SOTA methods. **a** Input **b** HE (González and Woods 1981), **c** SSR (Jobson et al. 1997a), **d** CVC (Çelik and Tjahjadi 2011), **e** MSRCR (Rahman et al. 2004), **f** Dong (Dong et al. 2011), **g** LIME (Guo et al. 2017), **h** Ours

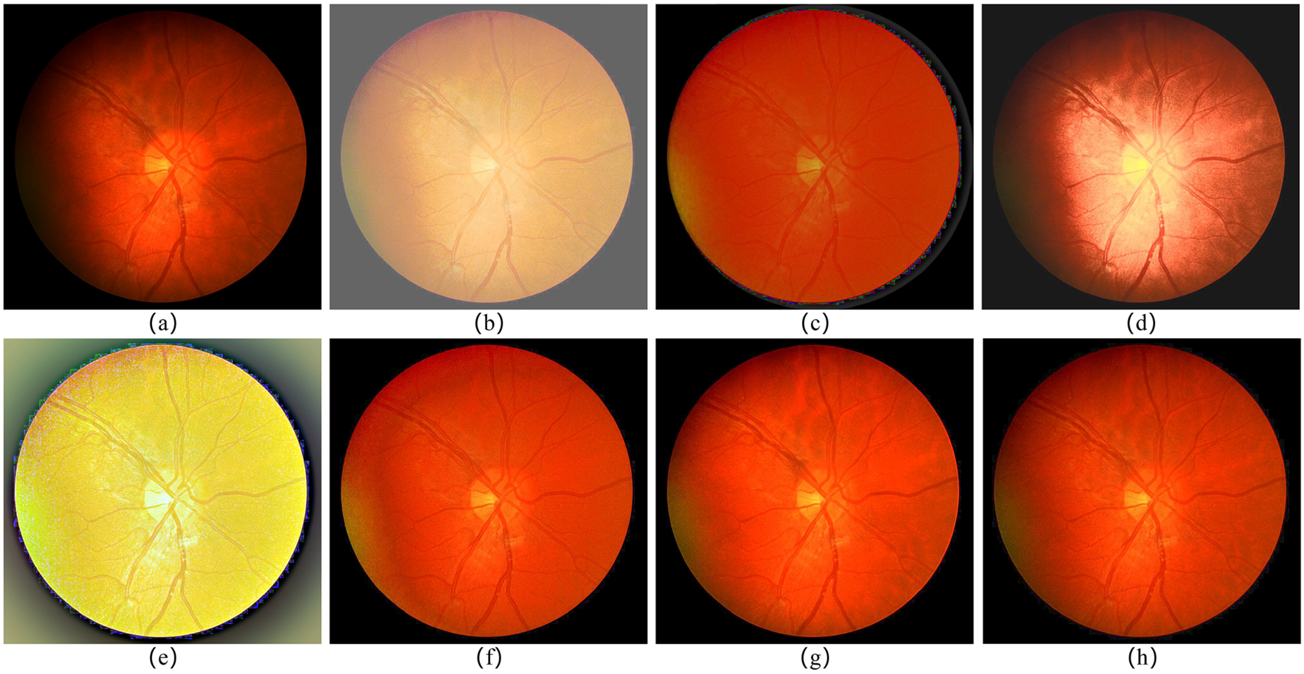

Fig. 3 Visual evaluation of an exemplar in CHASE_BD1 Zhang et al. (2016) dataset with the SOTA methods. **a** Input **b** HE (González and Woods 1981), **c** SSR (Jobson et al. 1997a), **d** CVC (Çelik and Tjahjadi 2011), **e** MSRCR (Rahman et al. 2004), **f** Dong (Dong et al. 2011), **g** LIME (Guo et al. 2017), **h** Ours

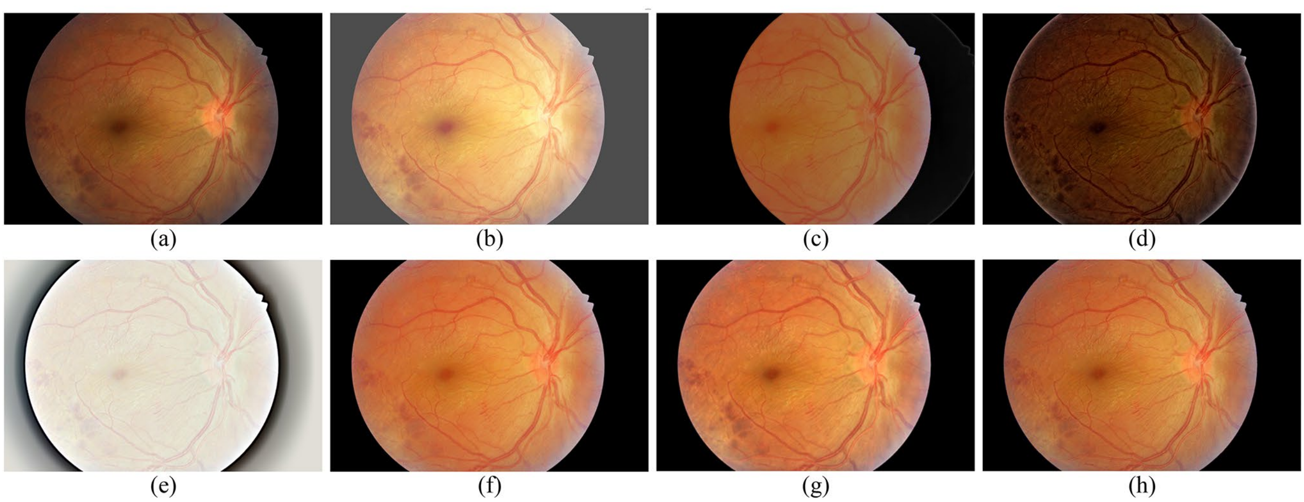

Fig. 4 Visual evaluation of an exemplar in IDRiD dataset with the SOTA methods. **a** Input **b** HE (González and Woods 1981), **c** SSR (Jobson et al. 1997a), **d** CVC (Çelik and Tjahjadi 2011), **e** MSRCR (Rahman et al. 2004), **f** Dong (Dong et al. 2011), **g** LIME (Guo et al. 2017), **h** ours

and noise. For example, HE (González and Woods 1981) performs well in darkness brightening, as shown in Fig.4b, but this global enhancement method may cause color distortion and blurring effect, *e.g.*, in Fig. 3b. The SSR (Jobson et al. 1997a) may cause the artifacts and insufficient illumination enhancement in the results. In Figs. 4c and 5c, the results generated by SSR (Jobson et al. 1997a) tend to be dislocated and ghosted. As stated in Figs. 4e and 5e, MSRCR (Rahman et al. 2004) can effectively improve the brightness, but results may tend to contain the color distortion. Besides, the high amount of mingled noise is introduced at the edge of eyes. CVC (Çelik and Tjahjadi 2011) method could enhance the low-light images with advisably detail preserved. Nevertheless, the enhanced images are

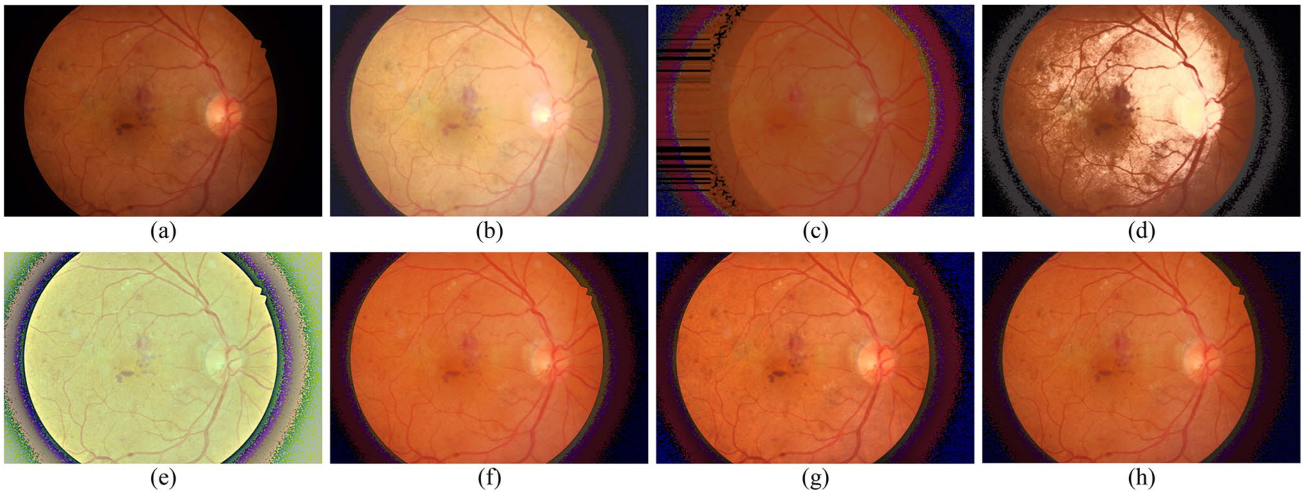

Fig. 5 Visual evaluation of an exemplar in IDRiD dataset with the SOTA methods. **a** Input **b** HE (González and Woods 1981), **c** SSR (Jobson et al. 1997a), **d** CVC (Çelik and Tjahjadi 2011), **e** MSRCR (Rahman et al. 2004), **f** Dong (Dong et al. 2011), **g** LIME (Guo et al. 2017), **h** ours

often suffered from color distortion and insufficient brightness. Although, the method such as Dong et al. (2011) and LIME (Guo et al. 2017) achieve the same results with the proposed method in Fig. 2f and g, these two methods could also bring noise and obscure at the edge of eyes as shown in Fig. 5f and g. Compared with the aforementioned methods, the proposed method could achieve satisfactory visual quality with relatively more natural and aesthetics subjective perception.

4.3 Quantitative evaluation

To verify the quantitative assessment, we employ three image quality assessment methods, namely natural image quality evaluator (NIQE) (Mittal et al. 2013), peak signal noise ration (PSNR) (Huynh-Thu and Ghanbari 2008; Wang et al. 2019), and structural similarity index measure (SSIM) (Wang et al. 2004). NIQE indicates the quality of the image by comparing the difference between the input image's feature distribution and the specific feature distribution. This distribution utilizes measurable deviations from statistical laws observed in natural images. A lower NIQE value means that the gap between the enhanced image and the natural image is smaller and the quality of the image is better. PSNR quantifies the degree that how the image is affected by noise, approximating the human perception of the image. For PSNR, the bigger value represents the better image quality. SSIM quantifies a measure or prediction of image quality relative to the original uncompressed or undistorted image as a reference. For SSIM, the bigger value represents the better image quality.

The quantitative comparative results among different methods on CHASE_BD1 and IDRiD are visible in Figs. 6 and 7. The numbers in the vertical axis represent the values of

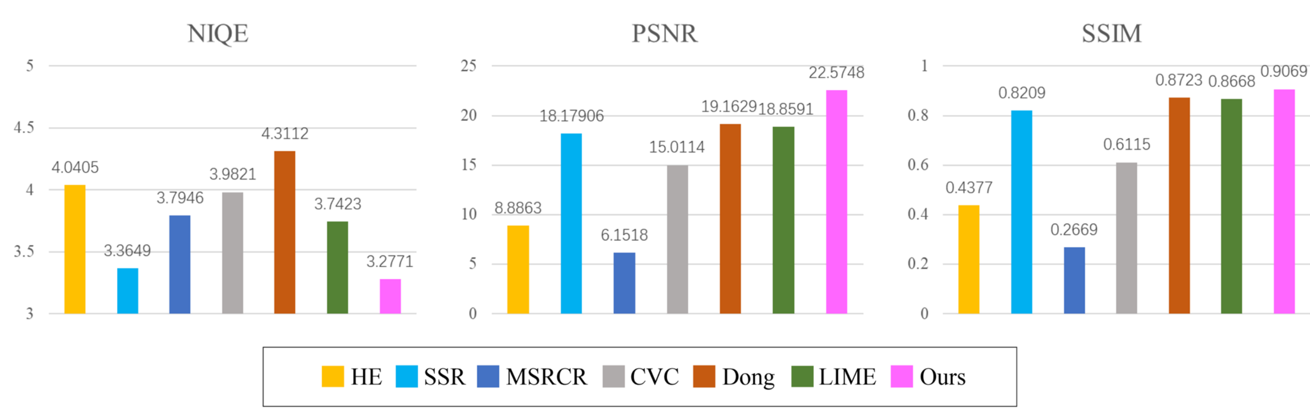

Fig. 6 Quantitative comparisons among different methods on CHASE_BD1 dataset

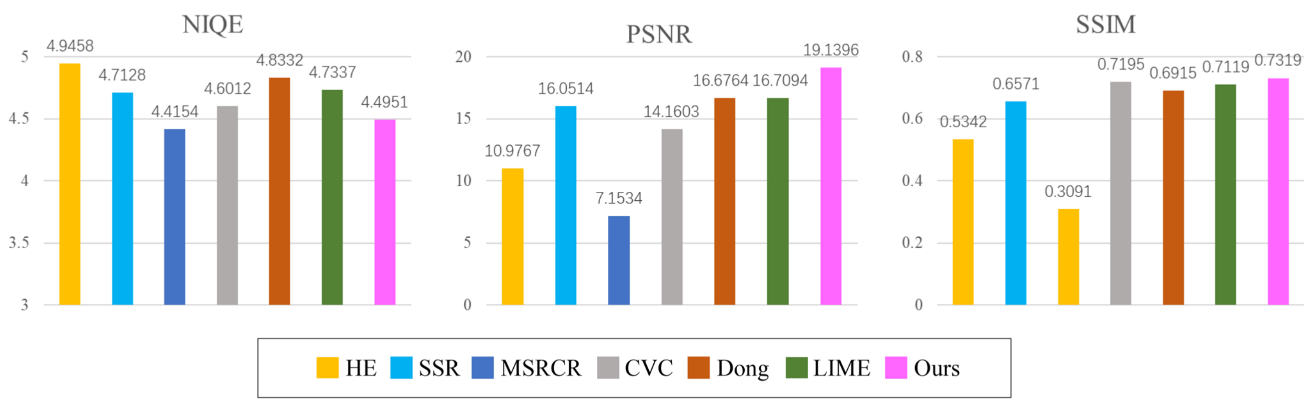

Fig. 7 Quantitative comparisons among different methods on IDRiD dataset

different competitors on the same quantitative assessment method. As demonstrated in Fig. 6, the CR2 outperforms the competitors on CHASE_BD1 dataset Zhang et al. (2016) in terms of NIQE, PSNR, and SSIM. In Fig. 7, it can be observed that the proposed method achieved the third-best score in NIQE, and the best score in PSNR and SSIM on IDRiD (Porwal et al. 2018) dataset, respectively. Although MSRCR (Rahman et al. 2004) achieves the best result in terms of NIQE on IDRiD (Porwal et al. 2018) dataset, it performs poorly on visual evaluation, as shown in Fig.5e.

As for the effectiveness verification of the proposed ADM optimization method, we measure the processing time of per single image in the CHASE_BD1 (Zhang et al. 2016) dataset. The CHASE_BD1 dataset consists of 14 pairs of retinal fundus images with a corresponding left (L) and right (R) label. We set the convergence condition as two-folds,

(i) $\|L_{k+1} - L_k\|_F / \|L_k\|_F \leq 10^{-3}$,
(ii) The maximum iteration number $K = 20$.

The comparison of processing time between ADM optimization method and alternative optimization method is shown in Fig. 8a. By comparing the processing speed, it can be observed that the proposed ADM optimization method can greatly reduce the time complexity.

The convergence curves of the illumination component on an RGB image from the CHASE_BD1 dataset is obtained by averaging the convergence error of ten times. The results are depicted in Fig. 8b. As demonstrated in Fig. 8b, with the increase of iteration number, the proposed ADM optimization method converges faster and reaches to a smaller error.

5 Conclusion

In this paper, we proposed an effective Complexity Reduction Retinex (CR^2) model to enhance the low luminance retinal fundus images. Unlike the traditional Retinex model, the regularization terms are adopted to ensure the spatial smoothness of the illumination map and the piece-wise continuousness of the reflectance map. We adopt the Alternating Direction Minimizing method to solve the complexity problem efficiently. Qualitative and quantitative evaluations on two public low luminance retinal fundus datasets have proven the superiority of the proposed method compared with the state-of-the-art methods.

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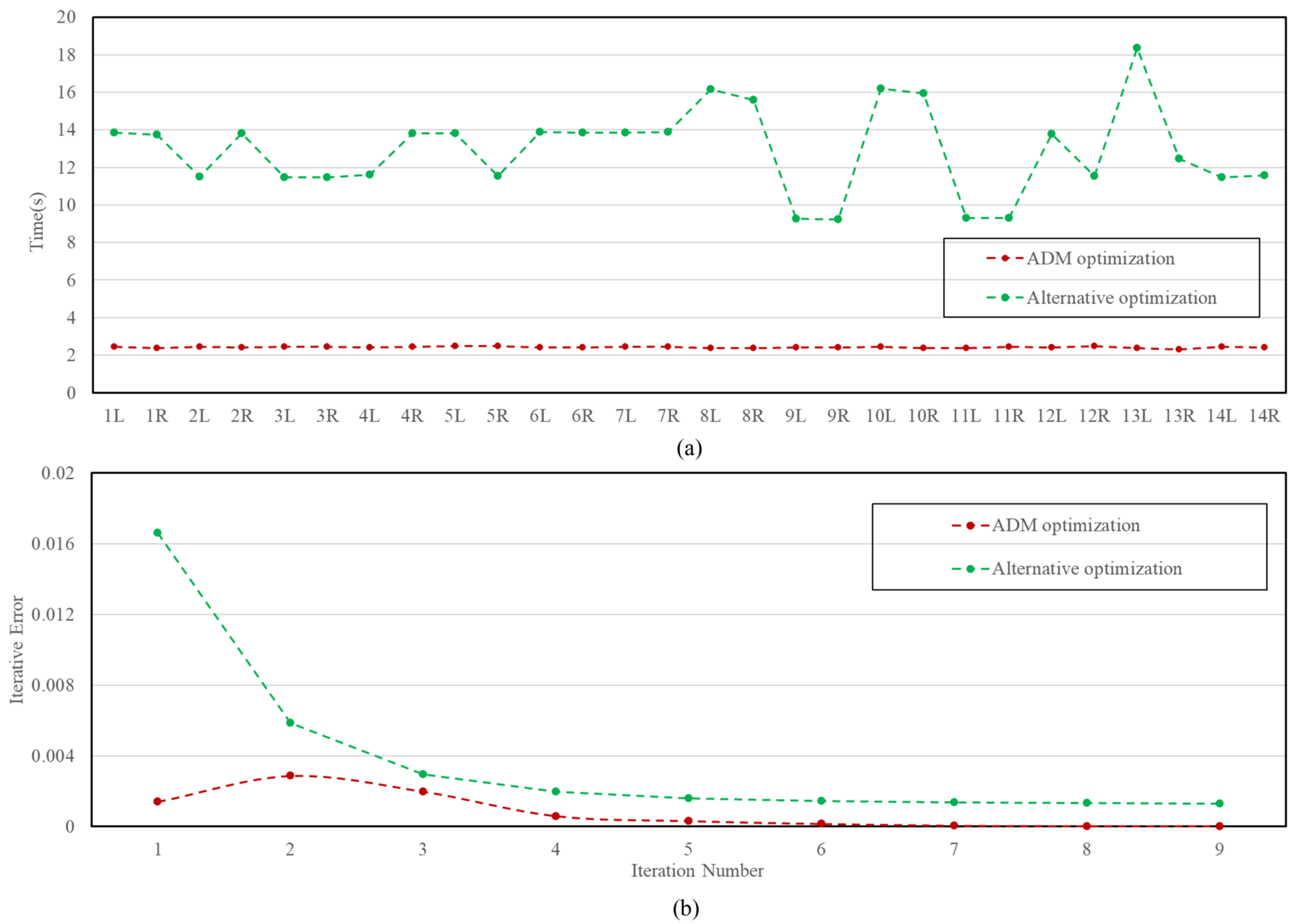

Fig. 8 The time complexity analysis. **a** The processed time comparison between ADM optimization method and the alternative optimization (Xu et al. 2020; Cai et al. 2017) on CHASE_BD1 dataset. **b** The convergence curves of illumination component's iterative error

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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