A variational framework for single low light image enhancement using bright channel prior

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***Abstract*—Low light image enhancement is prerequisite in many fields, such as surveillance systems, road safety and waterway transport. In this paper, a new variational framework using bright channel prior is proposed to address the low light image enhancement problem within a single image. An alternating direction optimization method is employed to solve the variational problem. Experiment results show that the new method can better eliminate the black halo and suppressing the issues of over-enhancement and color distortion when compared with other existing methods.**

***Index Terms*—low light image enhancement, Retinex, bright channel prior, alternating direction optimization, variational framework.**

I. Introduction

The quality of images and videos in low light condition is serious affected by the lack of light. It is important to enhance the low light images/videos in applications such as, surveillance systems, road safety and waterway transport. Recently, H. Ngo et al. enhance the low light videos using infrared cameras [1]. This method will fail when the temperature of objects is lower than its surroundings. The Multi-Scale Retinex [2] algorithm has a good performance in general. However, when the image is in very low light condition, the result looks like a gray image. Inspired by dark channel prior in image de-hazing [3], Dong et al. observed that the inverted low light image is similar to a hazy image [4]. De-hazing algorithm in [3] is applied to deal with the inversion of the low light video frames to obtain the enhancement results. However, when there is a bright spot, or the depth is not continuous in the low light image, there is black halo around these regions which affects visual result. In 2012, the algorithm in [4] is improved by using the luminance component to compute the transmission, then the joint-bilateral filter is adopted in the green channel of the enhanced image to reduce the noise [5]. The results look over-enhanced and have some color distortion due to the special processing in the green channel.

In this paper, a new variational framework for Retinex is proposed to enhance the single low light image, in which

1) the bright channel prior, which is proposed in our work [6] and other similar work [7], is introduced to eliminate the black halo and suppress the over-enhancement and color distortion;

2) there is no need to do the logarithmic transform, exponential transform, and Gamma-correction, reflection (enhanced image) and illumination image can be obtained simultaneously and directly;

3) alternating direction optimization method is applied to address the proposed objection function.

II. Motivation and problem formulation based on a novel variational Retinex model

The word of Retinex is synthesized by the retina and the cortex which is proposed by Land [8][9]. The Retinex theory considers that the human visual system can deal with illumination that changes both in brightness and color adaptively. The formulation of Retinex is $I = RL$, where I is the observed image, R is the reflectance which value is from 0 to 1, L is the illumination image and the multiplication is component-wise operator.

The variational Retinex model is firstly reported by Kimmel and Elad [10]:

$$\begin{aligned} \arg\min_{l} \int_{\Omega} (|\nabla l|^2 + \alpha(l-i)^2 + \beta|\nabla(l-i)|^2)dxdy \\ s.t.\ \ l \geq i,\ \langle \nabla l, \overrightarrow{n} \rangle = 0 \text{ on } \partial\Omega, \end{aligned} \tag{1}$$

where $i = \log I$, $l = \log L$, α and β are free non-negative real parameters. Ω is the support of the image, $\partial\Omega$ is the boundary, and $\overrightarrow{n}$ is the normal to the boundary. Illumination and reflectance is assumed to be piecewise smooth, as defined in the first term ($|\nabla l|^2$) and the third term ($|\nabla(l-i)|^2$), similarity between illumination and observed image is enforced based on a quadratic fidelity prior, as the second term ($(l-i)^2$). The problem is solved using the Euler-Lagrange equations.

In 2013, Zosso et al. proposed another variational Retinex model [11]:

$$\begin{aligned} \arg\min_{r} \|\nabla r - \nabla i\|_2^2 + \alpha \|r\|_2^2 + \beta \|\nabla r\|_2^2 \\ s.t.\ \ r \leq 0,\ \langle \nabla r, \overrightarrow{n} \rangle = 0 \text{ on } \partial\Omega, \end{aligned} \tag{2}$$

where $r = \log R$. This model rewrite the previous equation (1) to solve the reflectance instead of the illumination.

In this paper, we establish a novel variational Retinex model using the bright channel prior as follows:

$$\begin{aligned} \arg\min_{R,L} \|RL - I\|_2^2 + \alpha \|\nabla L\|_2^2 + \beta \|\nabla R\|_2^2 \\ +\gamma \|L - I_{bright}\|_2^2 \quad s.t. \quad I \leq L, \end{aligned} \tag{3}$$

where α, β and γ free non-negative real parameters. $\nabla L = (\partial_h L, \partial_v L)^T$ and $\nabla R = (\partial_h R, \partial_v R)^T$ are corresponding gradients, the operation is calculated as difference between neighboring pixels along the horizontal and vertical directions for each pixel. The first penalty term ($\|RL - I\|_2^2$) constrains proximity between (RL) and I. The second penalty term ($\|\nabla L\|_2^2$) constrains spatial smoothness on the illumination and is weighted by α. The third penalty term ($\|\nabla R\|_2^2$) constrains spatial smoothness on the enhanced image, which is weighted by β. The fourth term ($\|L - I_{bright}\|_2^2$), which is weighted by γ, constrains the illumination approximate the bright channel of I, which will be described later.

Inspired by the dark channel prior [3], we considered that in most of patches, at least one color channel has very high intensity at some pixels in a reflectance image (ideal image). The bright channel is proposed in our work [6] at first as follows:

$$R_{bright}(x) = \max_C(\max_{y \in \Omega(x)} R_C(y)), \tag{4}$$

where R is the reflectance image, C is the RGB-channel. R_C is a color channel of R, $\Omega(x)$ is local patch centered at x, R_{bright} is the bright channel of R. Using the concept of a bright channel, the intensity of R's bright channel tends to be 255: $R_{bright} \to 255$. We call this observation bright channel prior. Fig. 1 shows statistical data from 1000 high-quality images which is considered as ideal reflectance images. Fig. 2 shows some examples of bright channel. The experimental results verify the bright channel exists.

Since the illumination L is piece-wise smooth and we assume that L is constant in a local patch. We denote the patch's illumination as $\tilde{L}$. Taking the bright channel operation on the observed low light image I after normalization:

$$\max_C(\max_{y \in \Omega(x)} I_C(y)) = \max_C(\max_{y \in \Omega(x)} R_C(y))\,\tilde{L}(x), \tag{5}$$

$\tilde{L}$ can be put on the outside of the max operators as a constant. As R is a reflectance image, the bright channel of R is close to 1 after normalization due to the bright channel prior:

$$R_{bright}(x) = \max_C(\max_{y \in \Omega(x)} R_C(y)) = 1. \tag{6}$$

Putting (6) into (5), we can estimate the $\tilde{L}$ by:

$$\tilde{L}(x) = \max_C(\max_{y \in \Omega(x)} I_C(y)) \tag{7}$$

It provides the constraint of the illumination ($\|L - I_{bright}\|_2^2$) directly. Moreover, according to the prior, the value of R is from 0 to 1, the equation should subject to: $I \leq L$.

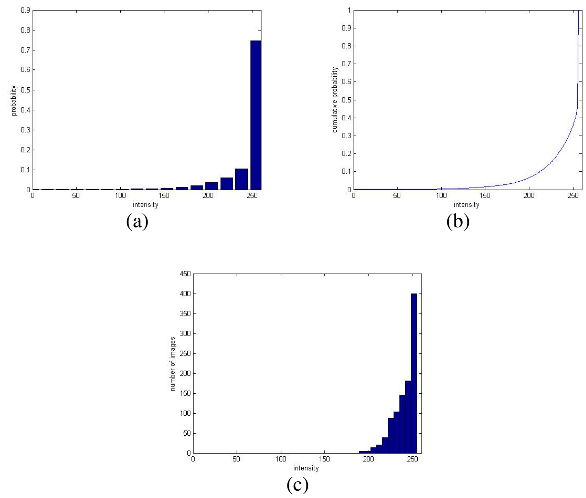


Fig. 1. Statistics of the bright channel. (a) histogram of the intensity of the pixels in all of the bright channels (each bin stands for 16 intensity levels). (b) corresponding cumulative distribution. (c) histogram of the average intensity of each bright channel.

Fig. 2. Examples of bright channel. Top: original images. Bottom: corresponding bright channels.

III. An Alternating Direction Optimization Method for the New Variational Model

As R and L in equation (3) are required to be solved simultaneously, traditional variational Retinex methods are not able to address it. An alternating direction optimization method is considered to calculate R and L iteratively. The main idea of this method is fixing one variable and updating another alternatively.

Step 1: calculate I_{bright} and initialize L First we compute the bright channel I_{bright} of the input low light image I and use the guided filter [12] to refine the edge. For the initialization of L, the Gaussian low-pass filtering is appropriately since the illumination has the property of piece-wise smoothness.

Step 2: calculate R After L is initialized and fixed, the equation (3) can be rewritten as:

$$\arg\min_R \left\| R - \frac{I}{L} \right\|_2^2 + \beta \|\nabla R\|_2^2. \tag{8}$$

Algorithm 1

1) **Input:** input low light image I, parameters α, β and γ.
2) **Initialization:** $L \leftarrow$ Gaussian filtering of I, $I_{bright} \leftarrow$ bright channel of I.
3) **for iter =1:n**.
   fixing L solve R in Eq.(9).
   fixing R, solve L in Eq.(11).
   correcting $L \leftarrow \max(L, I)$.
   end.
4) **Output:** enhanced image R and illumination image L.

The function is quadratic and thus has a global minimum. In order to avoid very-large-matrix inversion, we diagonalize derivative operators after FFT. The computing time is faster than in the image space by this operation.

The solution of R is:

$$R = \mathcal{F}^{-1}\left(\frac{\mathcal{F}(I/L)}{\mathcal{F}(1)+\beta(\mathcal{F}(\partial_h)^{*}\mathcal{F}(\partial_h) + \mathcal{F}(\partial_v)^{*}\mathcal{F}(\partial_v))}\right), \quad (9)$$

where $\mathcal{F}$ is the FFT operator and $F()^{*}$ is the complex conjugate, $\mathcal{F}(1)$ is the Fourier Transform of the delta function. All calculations are component-wise operators.

Step 3: calculate L After computing R, fixing it and rewriting equation (3) as:

$$\arg\min_{L} \left\| L - \frac{I}{R} \right\|_2^2 + \alpha \left\| \nabla L \right\|_2^2 + \gamma \left\| L - I_{bright} \right\|_2^2 . \quad (10)$$

The solution of L is:

$$L = \mathcal{F}^{-1}\left(\frac{\mathcal{F}(\gamma I_{bright} + I/R)}{\mathcal{F}(1+\gamma)+\alpha(F(\partial_h)^{*}\mathcal{F}(\partial_h) + \mathcal{F}(\partial_v)^{*}\mathcal{F}(\partial_v))}\right). \quad (11)$$

Step 4: correcting L According to the prior: $I \leq L$, we simply make a correction of L after it computed: $L = \max(L, I)$.

The new algorithm is shown in **Algorithm 1**. Both gray image and color image can be processed by our algorithm. Some experimental results will be shown and compared with other methods in next section.

IV. Experimental results and analysis

All the experimental images are processed by Matlab R2012a on a PC with a 2.60GHz Intel Pentium Dual Core Processor. We set α, β and γ to be 100, 0.1 and 0.9 respectively. The iteration number is 4-7. The patch size of the maximum filtering is 3×3. It takes about 2.2 seconds to process one color image with size of 720×540×3.

Fig. 3 is the experimental results of image "flower". Both illumination image and enhanced image can be obtained. As shown in Fig. 3, the detail of flowers, grass and ground can be seen clearly.

We show two comparisons with other two latest algorithms [4][5]. Fig. 4 shows the experimental results of image "snow mountain". It is clear that the method in [4] generate a black halo around the stars, as shown in the red box. The stars are treated as a bright spots, which cannot be removed precisely by de-hazing method after image inversion. The method in [5] does not have the black halo problem but its results exhibit over-enhancement, as shown in the green box, since the estimation of transmission is imprecise. Compared with other two methods, the new method has a significant improvement in subjective visual effect.

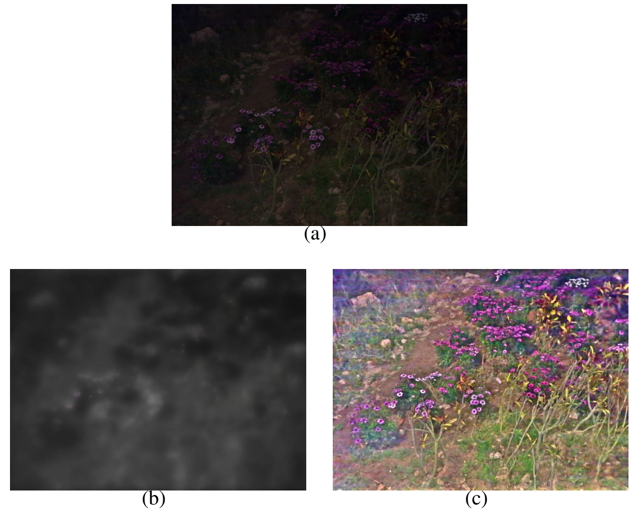


Fig. 3. the results of image "flower". (a) the input low light image. (b) the illumination image. (c) the enhanced image.

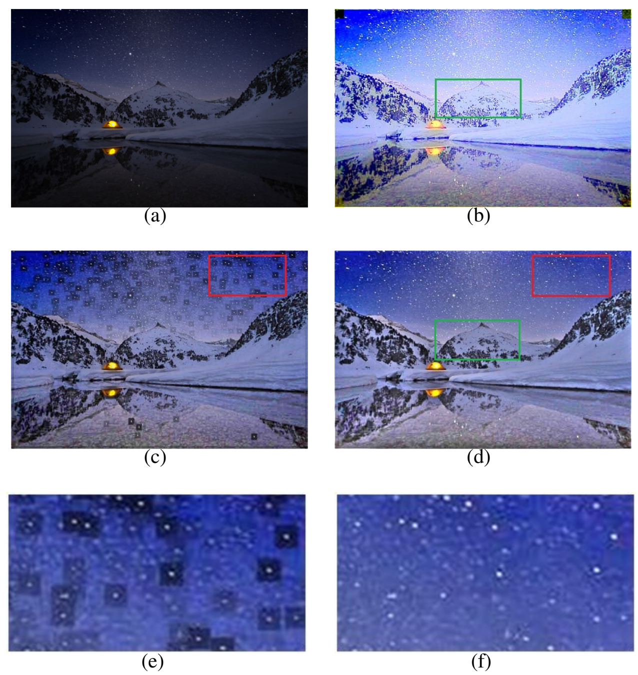
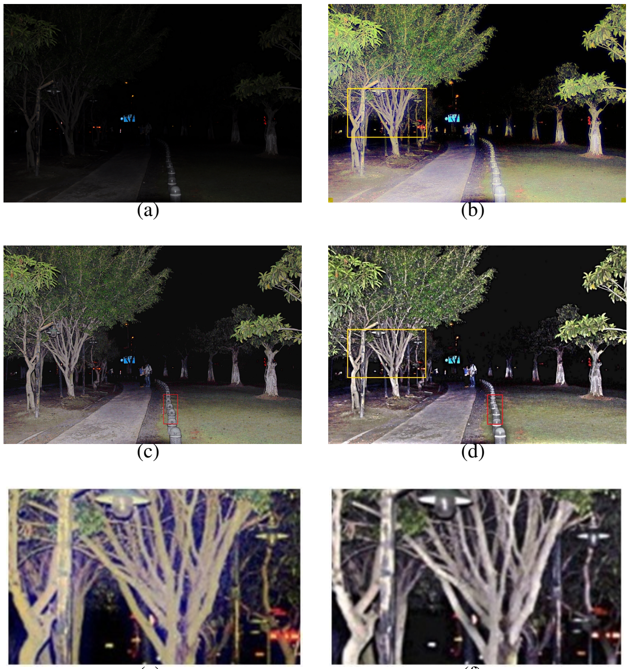


Fig. 4. The comparison of image "snow mountain". (a) the original low light image. (b) the result of Zhang's method [5]. (c) the result of Dong's method [4]. (d) the result by the new method. (e) zoomed-in part of (c) in the red box. (f) zoomed-in part of (d) in the red box.



(a) (b) (c) (d) (e) (f)

Fig. 5. The comparison of image "park". (a) the input low light image. (b) the result of Zhang's method [5]. (c) the result of Dong's method [4]. (d) the result by the new method. (e) zoomed-in part of (b) in the yellow box. (f) zoomed-in part of (d) in the yellow box.

Fig. 5 shows another experimental results of image "park". Dong's method [4] also has black halo in some bright spots as shown in the red box, meanwhile the result looks dim. In some regions, Zhang's method [5] has color distortion, as shown in the yellow box, since the operation of joint-bilateral filter is employed only in green channel, which makes the RGB-channel disproportion. The results of our new method is satisfactory in brightness, sharpness and color.

V. Conclusion

In this paper, a novel image enhancement method for single low light image is presented. The method introduces bright channel prior to the variational framework for Retinex. An effect and efficient alternation direction optimization method is employed to solve the model. Compared with other existing methods, experiment results demonstrated that the new method can eliminate the black halo and suppress the over-enhancement and color distortion.

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