Joint Denoising and Enhancement for Low-Light Images via Retinex Model

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Abstract. Guided by the Retinex model, image decomposition based low-light image enhancement methods attempt to manipulate the estimated illumination and project it back to the corresponding reflectance. However, the L2 constraint on the illumination often leads to halo artifacts, and the noise existed in the reflectance map is always neglected. In this paper, based on the Retinex model, we introduce a total variation optimization problem that jointly estimates noise-suppressed reflectance and piece-wise smooth illumination. The gradient of the reflectance is also constrained so that the contrast of the final enhancement result can be strengthened. Experimental results demonstrate the effectiveness of the proposed method with respect to low-light image enhancement.

Keywords: Low-light images, joint denoising and enhancement, Retinex model

1 Introduction

Images captured under low-light conditions suffer from many degradations, such as low visibility, low contrast, and high-level noise. Although these degradations can be somewhat alleviated by professional devices and advanced photographic skills, the inherent cause of the noise is unavoidable and can not be addressed at the hardware level. Without sufficient amount of light, the output of camera sensors is often buried in the intrinsic noise in the system. Longer exposure time can effectively increase the signal-to-noise ratio (SNR) and generate a noise-free image, however it breeds new problems such as motion blur. Thus, low-light image enhancement technique at the software level is highly desired in consumer photography. Moreover, such technique can also benefit many computer vision algorithms (object detection, tracking, *etc.*) since their performance highly relies on the visibility of the target scene.

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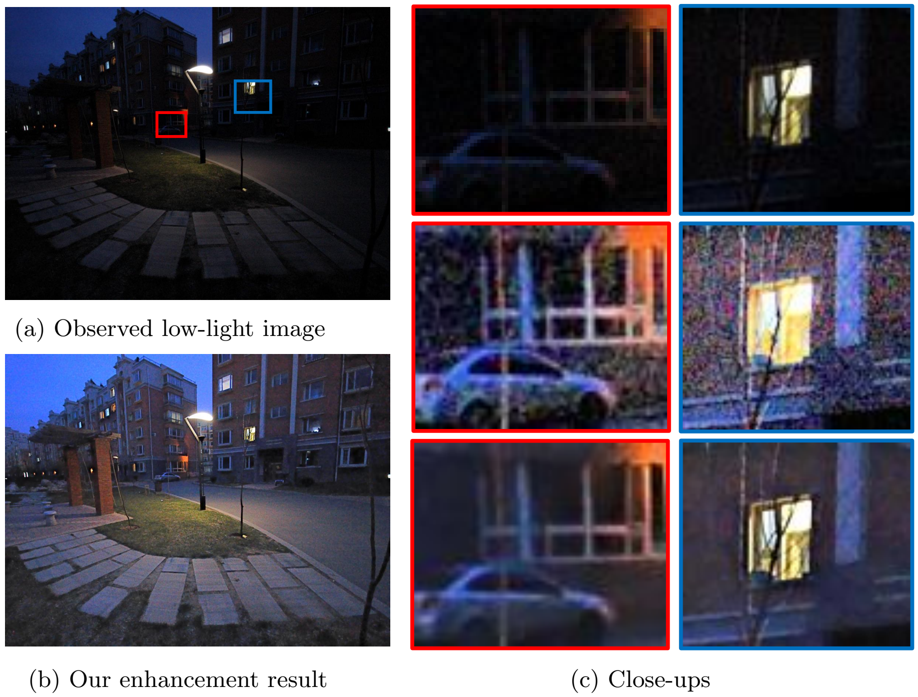


Fig. 1. (a) The observed low-light image. (b) The enhancement result of the proposed method. (c) Close-ups from top to bottom correspond to the input image, the enhancement result of the classic histogram equalization algorithm, and that of the proposed method. We can observe that the input image has low visibility and contrast. Intensive noise hidden in the observed image is revealed by histogram equalization. The proposed method generates visually pleasing results with better details and less noise.

However, this is not a trivial task, for that images captured under low-light conditions have rather low SNRs, which means the noises are highly intensive and may dominate over the image signals. Thus, low-light image enhancement algorithms need to tackle not only the low visibility, but also the high-level noises, in addition to low contrast (as illustrated in Fig. 1).

An intuitive way to enhance low-light images is to directly amplify the illumination. However, relatively bright areas may be saturated and some details might be lost through the operation. Histogram equalization (HE) based methods [1, 2], which aim to stretch the dynamic range of the observed image, can mitigate the problem to some extent. Nevertheless, their purpose is to enhance the contrast other than adjusting the illumination. Thus, results of these methods may be over- or under-enhanced. Furthermore, HE based methods neglect the intensive noise hidden in low-light images.

Some researchers [3, 4] noticed that the inverted low-light images look like haze images. Dehazing methods are therefore applied and the dehazing result is inverted once more as the enhancement result. A joint-bilateral filter is applied in [4] to suppress the noise after the enhancement. Li *et al.* [3] attempted to further improve the visual quality by segmenting the observed image into superpixels and adaptively denoising different segments via BM3D [5]. Although these methods can generate reasonable results, a convincing physical explanation of their basic model has not been provided. Moreover, the order of enhancing and denoising has always been a problem. Performing enhancement method before denoising may result in noise amplification, which increases the difficulty of denoising. On the other hand, enhancement results may be somewhat blurred after denoising.

Retinex theory [6] has been studied extensively in the past few decades, which assumes that images can be decomposed into two components, namely reflectance and illumination. Single-scale Retinex [7] and multiscale Retinex [8] are the pioneering studies in this field. They manipulate the illumination component and treat the reflectance as the final output. Wang *et al.* [9] proposed a bright-pass filter to decompose the observed image into reflectance and illumination, and attempted to preserve the naturalness while enhancing the image details. Based on the bright-pass filter proposed in [9], Fu *et al.* [10] fused multiple derivatives of the estimated illumination to combine different merits into a single output. The method proposed in [11] refines the initial illumination map by imposing a structure-aware prior. Nevertheless, due to the lack of constraint on the reflectance, these methods often amplify the latent intensive noise that exists in low-light images.

Although the logarithmic transformation is widely adopted for the ease of modeling by most Retinex based algorithms, a recent work [12] argues that the logarithmic transformation is not appropriate in the regularization terms since pixels with low magnitude dominate over the variation term in the high magnitude areas. Thus, a weighted variational model is proposed in [12] in order to impose better prior representation in the regularization terms. Even though this method shows rather impressive results in the decomposition of reflectance and illumination, the method is not suitable for the enhancement of low-light images as the noise often appears in low magnitude regions.

In this paper, instead of performing image enhancement and denoising separately, we present an optimization function designed for joint denoising and enhancement for low-light images. The rest of the paper is organized as follows: Sec. 2 introduces the proposed optimization problem that simultaneously estimates a noise-suppressed reflectance and a smoothed illumination map. Low-light enhancement results and analysis are presented in Sec. 3. Finally, Sec. 4 concludes the paper.

2 The Proposed Method

In this section, we propose a new optimization function that simultaneously estimates the reflectance $\mathbf{R}$ and the illumination $\mathbf{L}$ of the input image $\mathbf{I}$:

$$\underset{\mathbf{R},\mathbf{L}}{\operatorname{argmin}} \|\mathbf{R} \circ \mathbf{L} - \mathbf{I}\|_F^2 + \alpha \|\nabla \mathbf{R}\|_F^2 + \beta \|\nabla \mathbf{L}\|_1 + \omega \|\nabla \mathbf{R} - \mathbf{G}\|_F^2, \tag{1}$$

where α, β, and ω are the coefficients that control the importance of different terms. The operator $\circ$ denotes element-wise multiplication. $\|\cdot\|_F$ and $\|\cdot\|_1$ represent the Frobenius norm and ℓ_1 norm, respectively. In addition, ∇ is the first order differential operator, and $\mathbf{G}$ is the adjusted gradient of $\mathbf{I}$, which will be discussed in Equation (2). The role of each term in the objective (1) is interpreted below:

- $\|\mathbf{R} \circ \mathbf{L} - \mathbf{I}\|_F^2$ constrains the fidelity between the observed image $\mathbf{I}$ and the recomposed one $\mathbf{R} \circ \mathbf{L}$;
- $\|\nabla \mathbf{R}\|_F^2$ enforces the spatial smoothness on the reflectance $\mathbf{R}$, for that noise is often observed in the reflectance image;
- $\|\nabla \mathbf{L}\|_1$ corresponds to the total variation sparsity and considers the piece-wise smoothness of the illumination map $\mathbf{L}$;
- $\|\nabla \mathbf{R} - \mathbf{G}\|_F^2$ minimizes the distance between the gradient of the reflectance $\mathbf{R}$ and that of the observed image $\mathbf{I}$, so that the contrast of the final result can be strengthened.

As for the matrix $\mathbf{G}$, it is designed as the adjusted version of $\nabla \mathbf{I}$. The formulation of $\mathbf{G}$ is given as follows,

$$\mathbf{G} = \mathbf{K} \circ \nabla \hat{\mathbf{I}}, \tag{2}$$

$$\mathbf{K} = (1 + \lambda e^{-|\nabla \hat{\mathbf{I}}|/\sigma}), \tag{3}$$

where

$$\nabla \hat{\mathbf{I}} = \begin{cases} 0, & \text{if } |\nabla \mathbf{I}| < \varepsilon, \\ \nabla \mathbf{I}, & \text{otherwise.} \end{cases} \tag{4}$$

Specifically, after suppressing small gradients (*i.e.*, the noise), $\nabla \hat{\mathbf{I}}$ is amplified by the factor $\mathbf{K}$ that decreases with the increment of the gradient magnitude. Note that this amplification factor makes less adjustment in areas with higher gradient magnitude, while areas with lower gradient magnitude are strongly enhanced. So that after the amplification, the adjusted gradient $\mathbf{G}$ tends to have similar magnitude. Further, λ controls the degree of the amplification; σ controls the amplification rate of different gradients; ε is the threshold that filters small gradients. Images with higher noise levels often need a larger ε. In our experiments, parameters λ, σ, and ε are all set as 10. For each observed image, matrix $\mathbf{G}$ only needs to be calculated once.

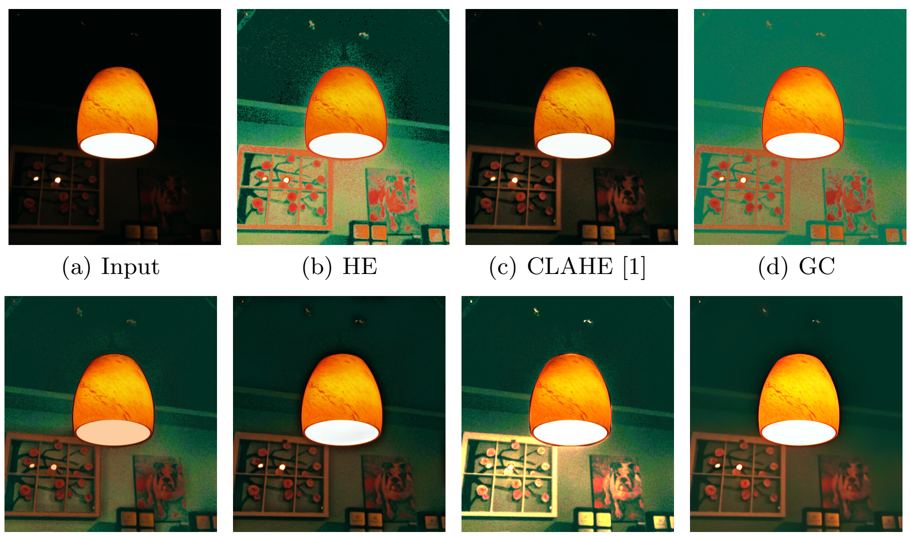
The optimization problem (1) can be effectively solved by the alternating direction minimization technique [13]. By substituting $\nabla \mathbf{L}$ in the third term with an auxiliary variable $\mathbf{T}$, the objective (1) can be rewritten in the following equivalent form:

$$\operatorname*{argmin}_{\mathbf{R},\mathbf{L},\mathbf{T}} \|\mathbf{R} \circ \mathbf{L} - \mathbf{I}\|_F^2 + \alpha\|\nabla \mathbf{R}\|_F^2 + \beta\|\mathbf{T}\|_1 + \omega\|\nabla \mathbf{R} - \mathbf{G}\|_F^2, \text{ s.t. } \quad \mathbf{T} = \nabla \mathbf{L}. \tag{5}$$

By introducing a Lagrange multiplier $\mathbf{Z}$ to remove the equality constraint, we have the augmented Lagrangian function of (5):

$$\begin{aligned}\mathcal{L}(\mathbf{R},\mathbf{L},\mathbf{T},\mathbf{Z}) = &\|\mathbf{R}\circ\mathbf{L}-\mathbf{I}\|_F^2 + \alpha\|\nabla\mathbf{R}\|_F^2 + \beta\|\mathbf{T}\|_1 \\ &+ \omega\|\nabla\mathbf{R}-\mathbf{G}\|_F^2 + \Phi(\mathbf{Z},\nabla\mathbf{L}-\mathbf{T}),\end{aligned} \tag{6}$$

where $\Phi(\mathbf{Z},\nabla\mathbf{L}-\mathbf{T}) = \langle\mathbf{Z},\nabla\mathbf{L}-\mathbf{T}\rangle + \frac{\mu}{2}\|\nabla\mathbf{L}-\mathbf{T}\|_F^2$ and $\langle\cdot,\cdot\rangle$ represents the matrix inner product. μ is a positive scalar. The equivalent objective function can be solved by iteratively updating each variable while regarding other variables that have been estimated in the previous iteration as constants.



(a) Input (b) HE (c) CLAHE [1] (d) GC

(e) NPE [9] (f) SRIE [12] (g) LIME [11] (h) Proposed

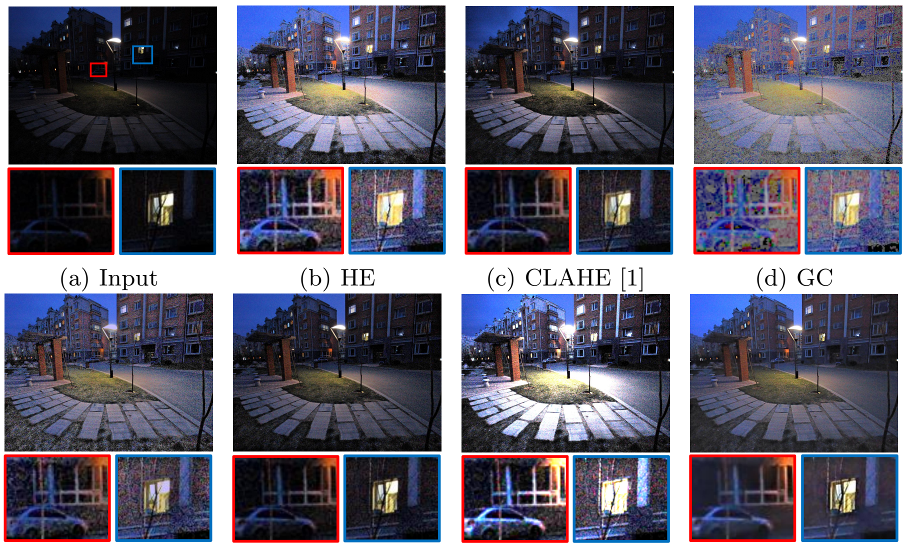
Fig. 2. Results comparison between different methods.

3 Experimental Results

In this section, we demonstrate low-light image enhancement results. All experiments are conducted in MATLAB R2015b on a PC running Windows 10 OS with 16G RAM and 3.5GHz CPU. In our experiments, the parameters α, β, and ω are empirically set as 0.001, 0.01, and 0.01, respectively.

After the estimation of the illumination $\mathbf{L}$ and the reflectance $\mathbf{R}$, the gamma correction operation is applied in order to adjust the illumination. And the final enhancement result $\mathbf{I}'$ is generated by:

$$\mathbf{I}' = \mathbf{R}\circ\hat{\mathbf{L}}^{\frac{1}{\gamma}}, \tag{7}$$



(a) Input (b) HE (c) CLAHE [1] (d) GC

(e) NPE [9] (f) SRIE [12] (g) LIME [11] (h) Proposed

Fig. 3. Results comparison between different methods.

where $\hat{\mathbf{L}}$ is the normalized $\mathbf{L}$, and γ is empirically set as 2.2.

We compare the proposed method with several state-of-the-art methods, including histogram equalization (HE), contrast limited adaptive histogram equalization (CLAHE) [1], gamma correction (GC), naturalness preserved enhancement algorithm (NPE) [9], simultaneous reflectance and illumination estimation (SRIE) [12], and low-light image enhancement via illumination map estimation (LIME) [11]. HE and CLAHE use the MATLAB built-in functions. GC is performed by $\mathbf{L}^{\gamma}$ with $\gamma = 5$. The codes of NPE, SRIE, and LIME are downloaded from the authors' websites. Test images come from LIME's website. In this work, we assume that each color channel has its own illumination and reflectance. Thus the proposed method is performed on different channels of the RGB input individually.

Figs. 2, 3 and 4 show several comparisons between enhancement results generated by different methods. As can be observed in Fig. 2, CLAHE and SRIE cannot effectively restore the details hidden by the insufficient illumination. S-RIE also generates halo artifacts. GC and LIME significantly improve the illumination, yet some parts of their results are over-enhanced. Although NPE shows comparable performance with the proposed method in these noise-free images, they fail to handle noisy cases. As shown in Fig. 3, the noise hidden in very low-light condition is really intense. After being processed by most of the enhancement methods, the noise is often highly amplified. It is observed that except for the proposed method, all the other methods generate noticeable noise.

Fig. 4. Comparison between different enhancement methods. (a)-(h): The input image, HE, CLAHE, SRIE, GC, LIME, NPE, and the proposed method.

(a) Input (b) HE (c) CLAHE [1] (d) GC

(e) NPE [9] (f) SRIE [12] (g) LIME [11] (h) Proposed

Fig. 5. Comparison of denoising results with the proposed method. (a) is the input image; (b)-(g) are enhancement results with a denoising procedure performed by BM3D with the denoising parameter $\sigma = 30$; (h) is the result obtained by the proposed method.

We also provide the comparison of the proposed method with the results of other methods post-processed by BM3D [5]. As shown in Fig. 5, BM3D successfully smoothes most of the amplified noise, but some details of the input image are also lost. By contrast, our result looks sharper and contains less noise.

4 Conclusion

The well-established Retinex model for intrinsic image decomposition faces challenges when being applied to low-light image enhancement due to the ignorance of the noise term. In this paper, we attempt to correct this point by introducing a noise term into the classic model. The new model naturally leads to a joint estimation for the reflectance and the illumination of the observed image. Specifically, the constraint on the gradient of the reflectance preserves the contrast of the final enhancement result. Experimental results show that our method can produce visually pleasing results for images captured under low-light situation.

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