Deep Retinex Decomposition for Low-Light Enhancement (Supplementary Material)

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Contents

1 LOL Dataset Implementation Details

We employ the following method to eliminate misalignments between the low/normal-light image pairs.

Step 1: Obtain two normal-light images, termed as N_1 and N_2.

Step 2: Change the exposure time and ISO to capture several low-light images.

Step 3: The exposure time and ISO are reset to original settings to obtain another two normal-light images N_3 and N_4.

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This work was supported by National Natural Science Foundation of China under contract No. 61772043. We also gratefully acknowledge the support of NVIDIA Corporation with the GPU for this research.

Parameter	Value
Exposure	$-5+5F$
Highlights	$50\min\{Y,0.5\}+75$
Shadows	$-100\min\{Z,0.5\}$
Vibrance	$-75+75F$
Whites	$16(5-5F)$

Table 1: Algorithms that we use to generate values for parameters provided by Adobe Lightroom. X, Y and Z obey uniform random distribution $U(0,1)$ and $F = X^2$.

The average of N_i $(i = 1,2,3,4)$, is treated as the ground-truth G:

$$G = \frac{1}{4}\sum_{i=1}^{4} N_i. \tag{1}$$

And the misalignment for each N_i in one pair is measured by the average mean squared error (MSE) M between N_i $(i = 1,2,3,4)$ and G as follows:

$$M = \frac{1}{4}\sum_{i=1}^{4} \mathrm{MSE}(N_i, G), \tag{2}$$

where

$$\mathrm{MSE}(N,G) = \frac{1}{n}\sum_{i=1}^{n}(N_i - G_i)^2. \tag{3}$$

When M is a large value, there are severe misalignments between the four normal-light images. Thus, the corresponding pairs should be removed from the dataset. In our work, the threshold is set to 0.1.

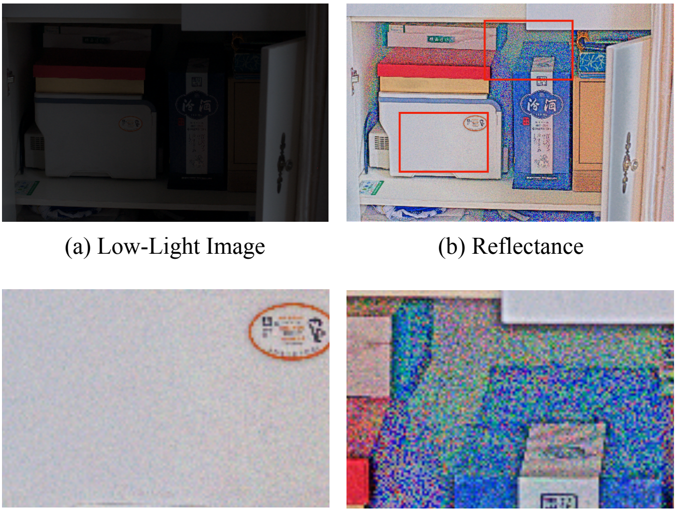
2 Parameter Configuration for Synthetic Image Pairs

Final parameter configuration is listed as follows. First, we generate three auxiliary factors X, Y, Z and F, where X, Y and Z obeys uniform random distribution $U(0,1)$ and $F = X^2$. Then, we generate parameters according to the algorithm given in Table 1.

3 Denoising Operation

BM3D is employed as the denoising operation for its outstanding performance in removing practical general noises. As shown in Figs. 2 and 3, the magnitude of noise is not the same in different regions. Noise in the dark region is amplified by dividing the illumination from the original image. To prevent over-smoothing in bright parts and keeping noise in dark parts, we adopt an illumination dependent denoising strategy. The following operation iterates over the decomposed result reflectance R:

$$\begin{aligned} M_t &= \mathrm{clip}(I,0,UB_t)/UB_t, && (4)\\ M'_t &= M_t^{\alpha_t}, && (5)\\ R_t &= R_{t-1}\times M'_t + \mathrm{BM3D}(R,\sigma_t)\times(1-M'_t), && (6) \end{aligned}$$



(a) Low-Light Image (b) Reflectance

Noise Level: 19.725
(c) Brighter part

Noise Level: 41.305
(d) Darker part

Figure 1: We further estimate the noise level using [4]. The magnitude of noise in darker regions is greater than that in brighter regions.

where I represents decomposed result illumination, R_t represents the reflectance after each iteration t and R_0 is R, BM3D($\cdot$) represents the BM3D algorithm and σ_t is a parameter for it. Eq.(4) and Eq.(5) generate an illumination guidance map for Eq.(6). Eq.(4) deletes already-cleaned areas and Eq.(5) strengthens noisy areas. In Eq.(6), darker areas are denoised by BM3D and combined with the current reflectance. Finally the operation is iterated 3 times, with $UB_1 = 1$, $\alpha_1 = 1$, $\sigma_1 = 10$, $UB_2 = 0.08$, $\alpha_2 = 10$, $\sigma_2 = 20$, $UB_3 = 0.03$, $\alpha_3 = 100$ and $\sigma_3 = 40$.

4 More Decomposition Results

We illustrate more decomposition results, comparing with SRIE [2] and LIME [3]. As shown in Fig. 2, our method produces similar reflectance extracted from low/normal-light images in both smooth and textual regions. Illumination produced by our method can capture image structures better and leave less illumination variation on reflectance. It is interesting to note that in extreme low-light regions, the reflectance tends to be greenish in both SRIE, LIME and our results, which indicates the higher intensity of green channel of RGB images in dark regions.

5 More Experimental Results

We now provide more results on real-scene images from public MEF [5], NPE [8], and Fusion [7] dataset. MEF contains 17 image sequences with multiple exposure levels. NPE contains 8 nature scene images used in [8], and three supplementary datasets contain another

77 images. Fusion contains 20 testing images. We compare our Retinex-Net with four state-of-the-art methods, including de-hazing based method (DeHz) [1], naturalness preserved enhancement algorithm (NPE) [8], simultaneous reflectance and illumination estimation algorithm (SRIE) [2], and illumination map estimation based (LIME) [3]. As displayed in Figs. 4 to 7, our method suffers from less over-exposure around light areas like lamps and dark edges, and brightens up details buried in dark regions.

6 More Joint Denoising Experimental Results

We now provide more joint denoising results comparing with LIME and JED [6], a recent joint low-light enhancement and denoising method. As displayed in Fig. 8, Our method preserves details better, and removes noise well at the same time.

References

[1] Xuan Dong, Guan Wang, Yi Pang, Weixin Li, Jiangtao Wen, Wei Meng, and Yao Lu. Fast efficient algorithm for enhancement of low lighting video. In *IEEE International Conference on Multimedia and Expo*, pages 1–6, 2011.

[2] Xueyang Fu, Delu Zeng, Yue Huang, Xiao Ping Zhang, and Xinghao Ding. A weighted variational model for simultaneous reflectance and illumination estimation. In *IEEE International Conference on Computer Vision and Pattern Recognition*, pages 2782–2790, 2016.

[3] Xiaojie Guo, Yu Li, and Haibin Ling. Lime: Low-light image enhancement via illumination map estimation. *IEEE Transactions on Image Processing*, 26(2):982–993, 2017.

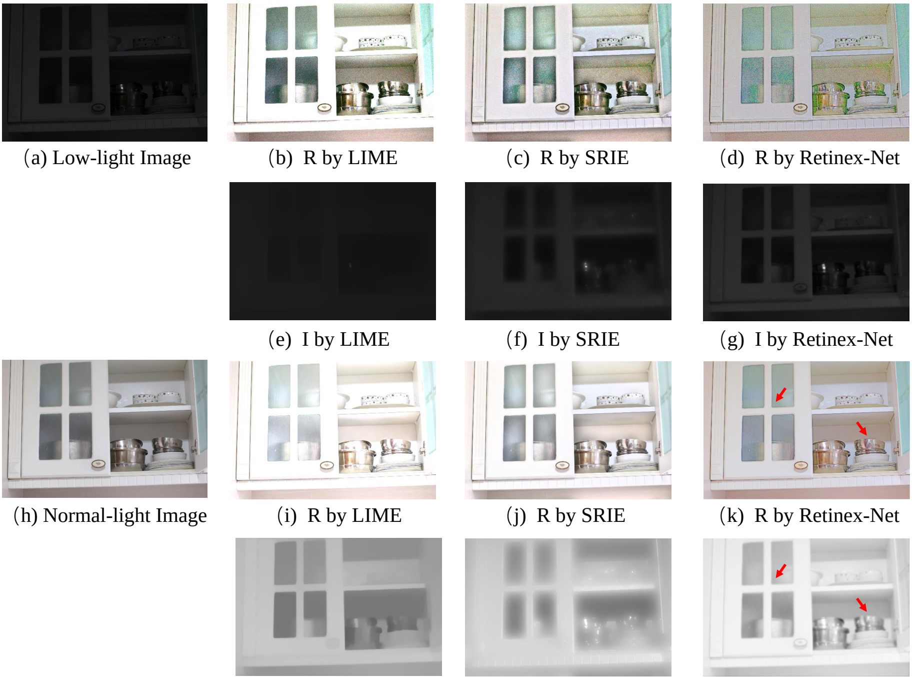
[4] Xinhao Liu, Masayuki Tanaka, and Masatoshi Okutomi. Noise level estimation using weak textured patches of a single noisy image. In *IEEE International Conference on Image Processing*, pages 665–668, 2012.

[5] Keda. Ma, Kai. Zeng, and Zhou. Wang. Perceptual quality assessment for multi-exposure image fusion. *IEEE Transactions on Image Processing*, 24(11):3345, 2015.

[6] Xutong Ren, Mading Li, Wen-Huang Cheng, and Jiaying Liu. Joint enhancement and denoising method via sequential decomposition. *IEEE International Symposium on Circuits and Systems*, 2018.

[7] Qiuhong Wang, Xueyang Fu, Xiao-Ping Zhang, and Xinghao Ding. A fusion-based method for single backlit image enhancement. In *IEEE International Conference on Image Processing*, pages 4077–4081, 2016.

[8] Shuhang Wang, Jin Zheng, Hai Miao Hu, and Bo Li. Naturalness preserved enhancement algorithm for non-uniform illumination images. *IEEE Transactions on Image Processing*, 22(9):3538–48, 2013.



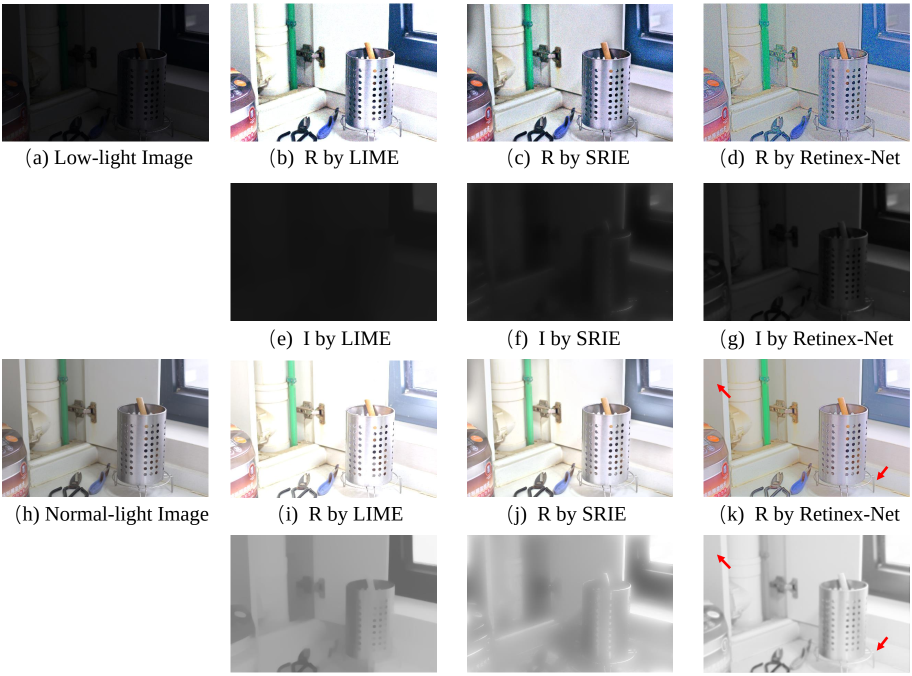
(a) Low-light Image (b) R by LIME (c) R by SRIE (d) R by Retinex-Net

(e) I by LIME (f) I by SRIE (g) I by Retinex-Net

(h) Normal-light Image (i) R by LIME (j) R by SRIE (k) R by Retinex-Net

(l) I by LIME (m) I by SRIE (n) I by Retinex-Net

Figure 2: More decomposition results compared with SRIE and LIME.



(a) Low-light Image (b) R by LIME (c) R by SRIE (d) R by Retinex-Net

(e) I by LIME (f) I by SRIE (g) I by Retinex-Net

(h) Normal-light Image (i) R by LIME (j) R by SRIE (k) R by Retinex-Net

(l) I by LIME (m) I by SRIE (n) I by Retinex-Net

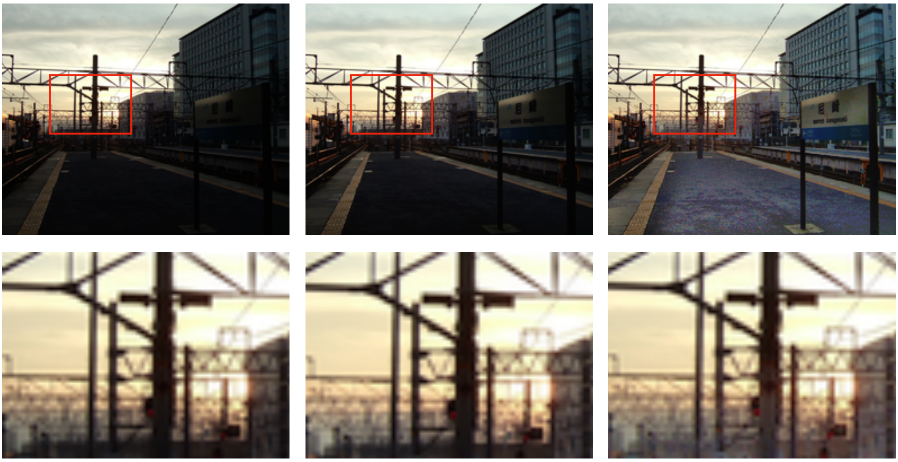
Figure 3: More decomposition results compared with SRIE and LIME.

Figure 4: The results using different methods on *Farm house* in MEF Dataset.

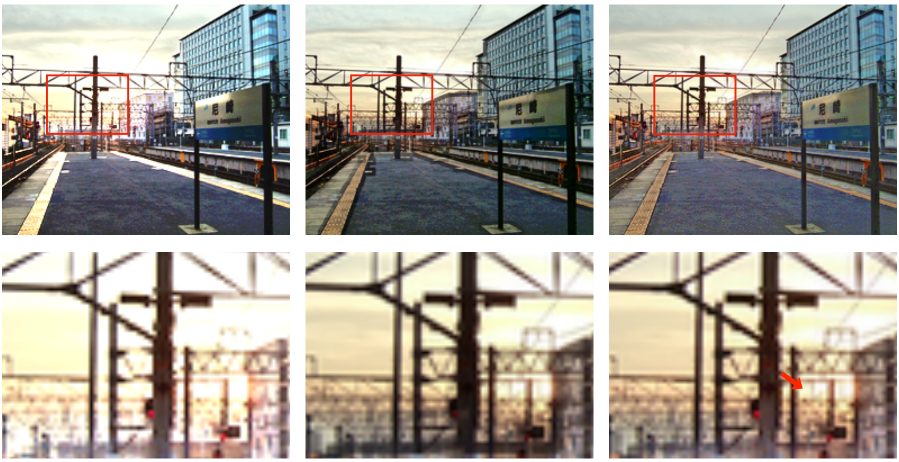
(a) Input (b) SRIE (c) NPE

(d) LIME (e) DeHz (f) Retinex-Net

Figure 5: The results using different methods on *Day break* in NPE Dataset.



(a) Input (b) SRIE (c) NPE



(d) LIME (e) DeHz (f) Retinex-Net

Figure 6: The results using different methods on *Platform* in Fusion Dataset.

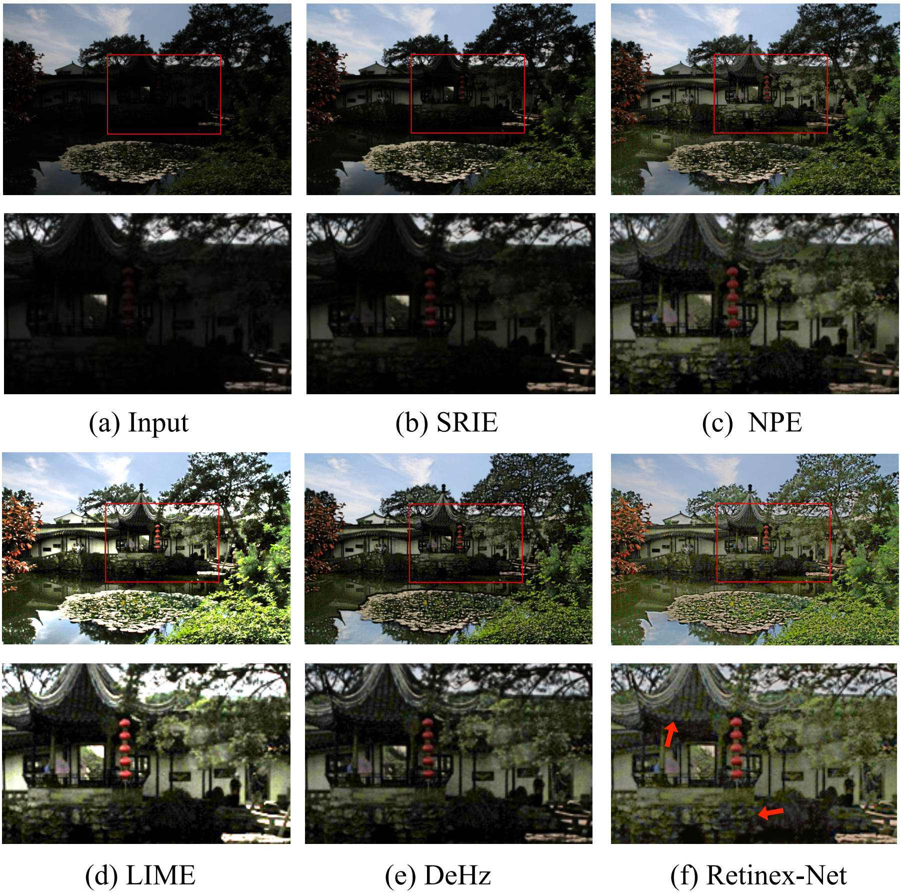


Figure 7: The results using different methods on *Chinese garden* in MEF Dataset.

(a) LIME (b) JED (c) Retinex-Net

Figure 8: The joint denoising results using different methods on natural images: (top-to-bottom) *Shower head* and *Carton* from LOL Dataset.