From Fidelity to Visual Quality: A Semi-Supervised Approach for Low-Light Image Enhancement (Supplementary Material)

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Abstract

This supplementary material presents the ablation study of recursive band learning (the first stage of proposed deep recursive band network) and band recomposition (its second stage), the visualization results of the learned bands, and more visual comparisons. The compared methods include Bio-Inspired Multi-Exposure Fusion (BIMEF) [14], Brightness Preserving Dynamic Histogram Equalization (BPDHE) [5], Camera Response Model (CRM) [16], Differential value Histogram Equalization Contrast Enhacement (DHECE) [10], Dong [1], Exposure Fusion Framework (EFF) [15], Contrast Limited Adaptive Histogram Equalization (CLAHE) [17], Low-Light Image Enhancement via Illumination Map Estimation (LIME) [4], Multiple Fusion (MF) [2], Multiscale Retinex (MR) [7] Joint Enhancement and Denoising Method (JED) [11], Refined Retinex Model (RRM) [9], Simultaneous Reflectance and Illumination Estimation (SRIE) [3], Deep Retinex Decomposition (DRD) [13], Deep Underexposed Photo Enhancement (DeepUPE) [12], EnlightenGAN [6].

1. Ablation Study for Recursive Band Learning

We perform the ablation studies for Recursive Band Learning quantitatively. Five versions are compared.

- *Version 1* (*RBL-v1*) does not include the recursive processing (only once prediction) and multi-scale loss constraint, by replacing Eqn. (7) in the main submission as follows,

$$L_{\text{Rect}} = -\phi\left(\hat{x}^T_{s_1}, x\right). \tag{1}$$

- *Version 2* (*RBL-v2*) additionally includes the multi-scale loss constraint.
- *Version 3* (*RBL-v3*) includes the recursive processing but without the feature bypass connection and the recursive input, by replacing Eqn. (6) in the main submission as follows,

$$\begin{aligned}
\left[\Delta f^t_{s_1},\ \Delta f^t_{s_2}, \Delta f^t_{s_3}\right] &= F^t_{\text{BLN_F}}\left(\hat{x}^{t-1}_{s_1}\right),\\
f^t_{s_i} &= \Delta f^t_{s_i}, i = 1, 2, 3,\\
\hat{x}^t_{s_3} &= F^t_{\text{R_}s_3}\left(f^t_{s_3}\right),\\
\hat{x}^t_{s_2} &= F^t_{\text{R_}s_2}\left(f^t_{s_2}\right) + F_{\text{U}}\left(\hat{x}^t_{s_3}\right),\\
\hat{x}^t_{s_1} &= F^t_{\text{R_}s_1}\left(f^t_{s_1}\right) + F_{\text{U}}\left(\hat{x}^t_{s_2}\right).
\end{aligned} \tag{2}$$

- *Version 4* (*RBL-v4*) includes the recursive processing and the recursive input by without the feature bypass connection, by replacing Eqn. (6) in the main submission as follows,

$$\begin{aligned}
\left[\Delta f^t_{s_1},\ \Delta f^t_{s_2}, \Delta f^t_{s_3}\right] &= F^t_{\text{BLN_F}}\left(y, \hat{x}^{t-1}_{s_1}\right),\\
f^t_{s_i} &= \Delta f^t_{s_i}, i = 1, 2, 3,\\
\hat{x}^t_{s_3} &= F^t_{\text{R_}s_3}\left(f^t_{s_3}\right),\\
\hat{x}^t_{s_2} &= F^t_{\text{R_}s_2}\left(f^t_{s_2}\right) + F_{\text{U}}\left(\hat{x}^t_{s_3}\right),\\
\hat{x}^t_{s_1} &= F^t_{\text{R_}s_1}\left(f^t_{s_1}\right) + F_{\text{U}}\left(\hat{x}^t_{s_2}\right).
\end{aligned} \tag{3}$$

- *Version 5* (*RBL-v5*) is the full version and includes the recursive processing, recursive input and feature bypass connection.

To better reflect the average performance of the five versions, we calculate their average performance in the last 50 epochs (250-300 epochs). The results are presented in Table 1. Comparing RBL-V1 to RBL-V2, it is observed that, the multi-scale loss leads to performance gains in PSNR and SSIM. Comparing RBL-V3 and RBL-V4 to RBL-V2, we can observe that, the recursive structure might not achieve an improved performance, as RBL-V3 and RBL-V4 have performance drops in PSNR and SSIM, respectively. With both the recursive input and bypass connection, RBL-V5 obtains significant gains and best results in PSNR and SSIM, which demonstrates the effectiveness and rationality of our RBL.

Table 1. The ablation study for recursive band learning (RBL).

Metrics	RBL-v1	RBL-v2	RBL-v3	RBL-v4	RBL-v5
PSNR	18.52	19.07	19.33	18.51	**19.71**
SSIM	0.8638	0.8679	0.8413	0.8744	**0.8853**

2. Visual Comparisons

We provide more visual results in Figs. 1-5. In general, most of previous methods fail to well restore global illumination and structures. DHECE, LIME, NPE, and EnlightenGAN well restore the global illumination of the results. However, in their results, the burred noise is amplified, which heavily impairs the local details. RRM, MF, JED, and UPE suffer form under-exposure and poor visibility. In their Gamma corrected results (right parts), noise is seldom observed in the results of RRM and JED. However, contrast of these two methods is not promising. Comparatively, our method achieves very good perceptual visual quality, with good illumination, color distribution, as well as clean and sharp details.

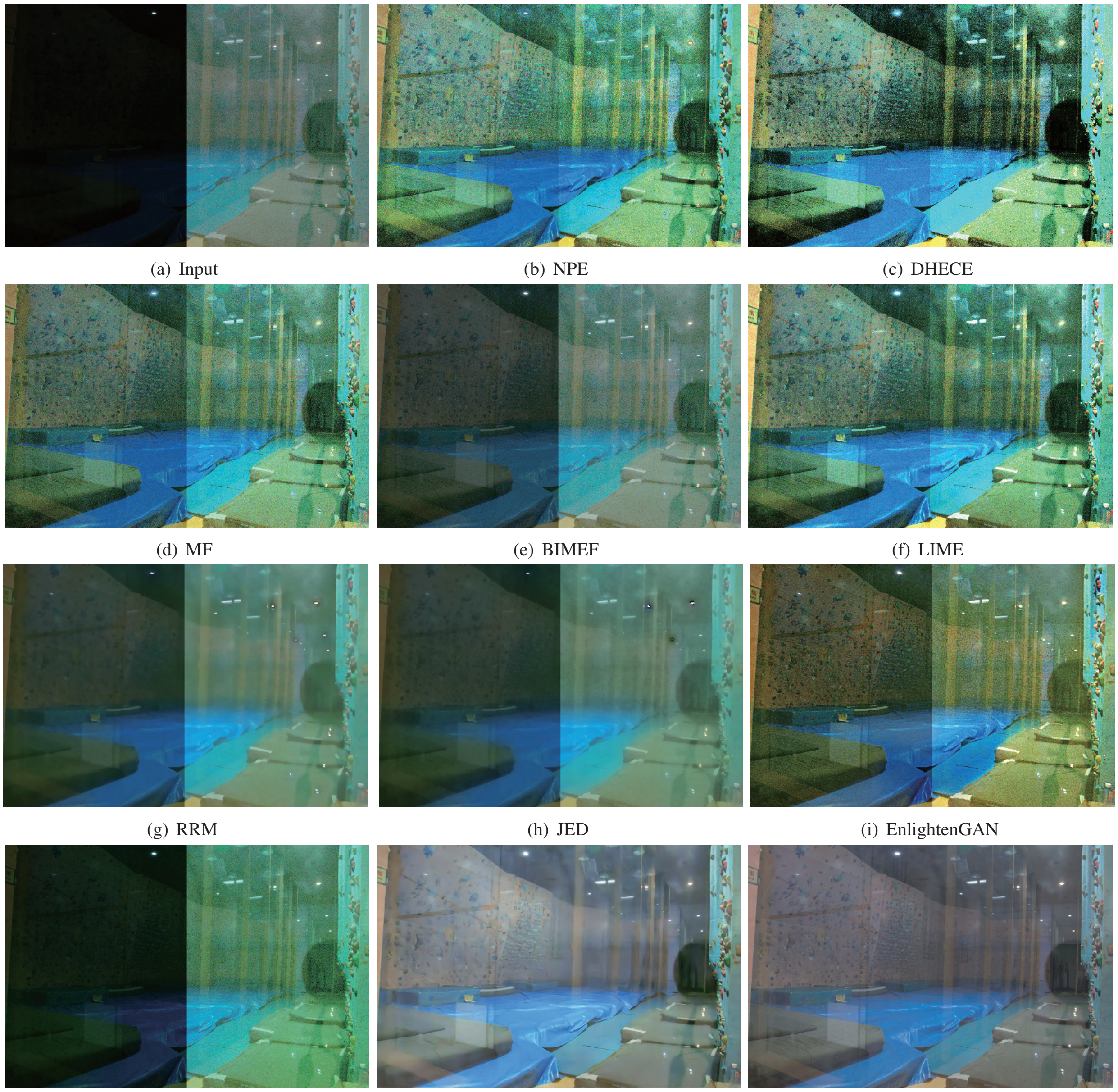
(a) Input (b) NPE (c) DHECE

(d) MF (e) BIMEF (f) LIME

(g) RRM (h) JED (i) EnlightenGAN

(j) UPE (k) DRBN (l) GT

Figure 1. The visual results of different methods on an input image from LOL dataset [13]. Left part: the original results. Right part: the results corrected by Gamma transformation for better visibility. Zooming-in the figure will provide a better look at the restoration quality.



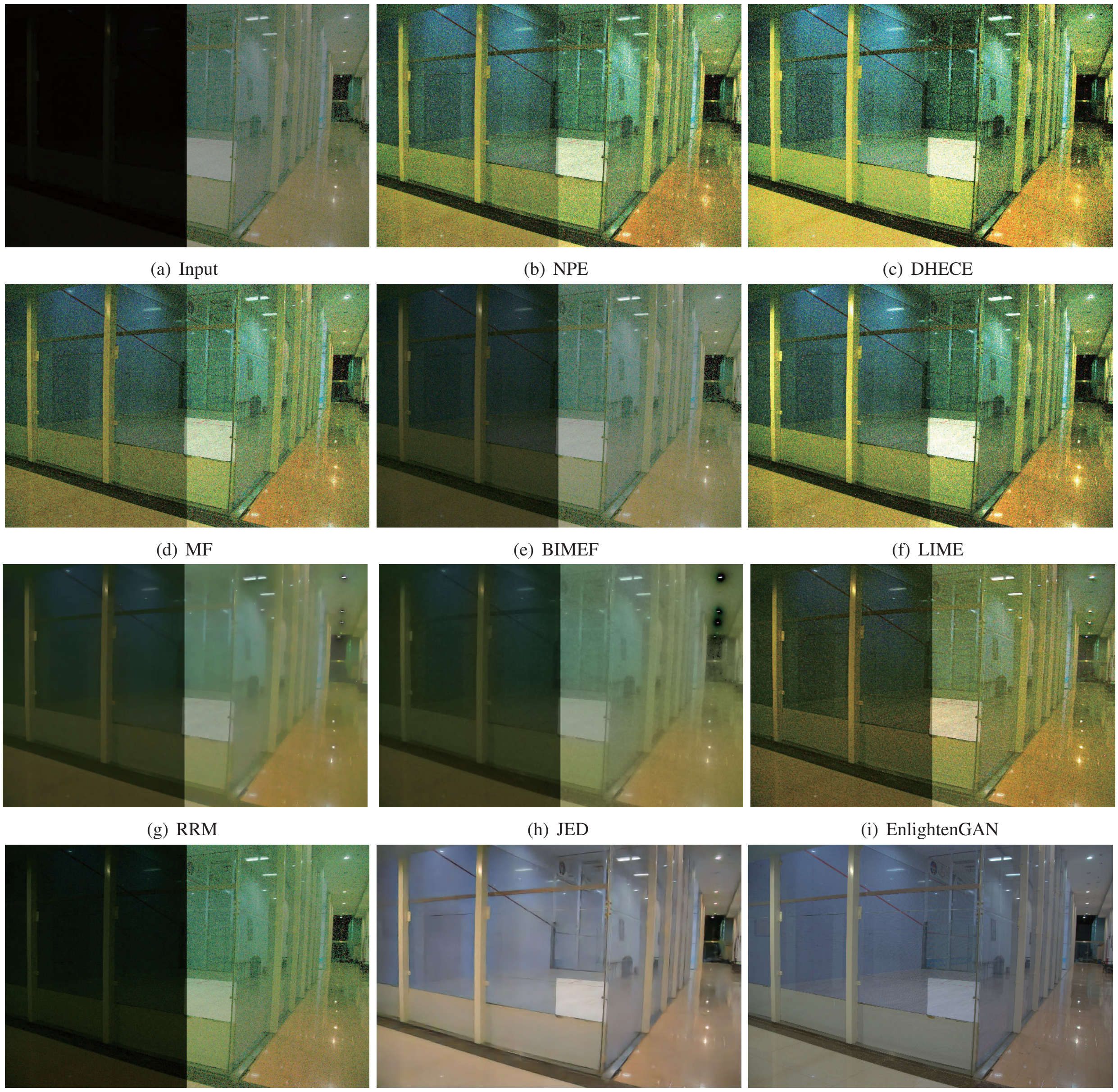
(a) Input (b) NPE (c) DHECE

(d) MF (e) BIMEF (f) LIME

(g) RRM (h) JED (i) EnlightenGAN

(j) UPE (k) DRBN (l) GT

Figure 2. The visual results of different methods on an input image from LOL dataset [13]. Left part: the original results. Right part: the results corrected by Gamma transformation for better visibility. Zooming-in the figure will provide a better look at the restoration quality.

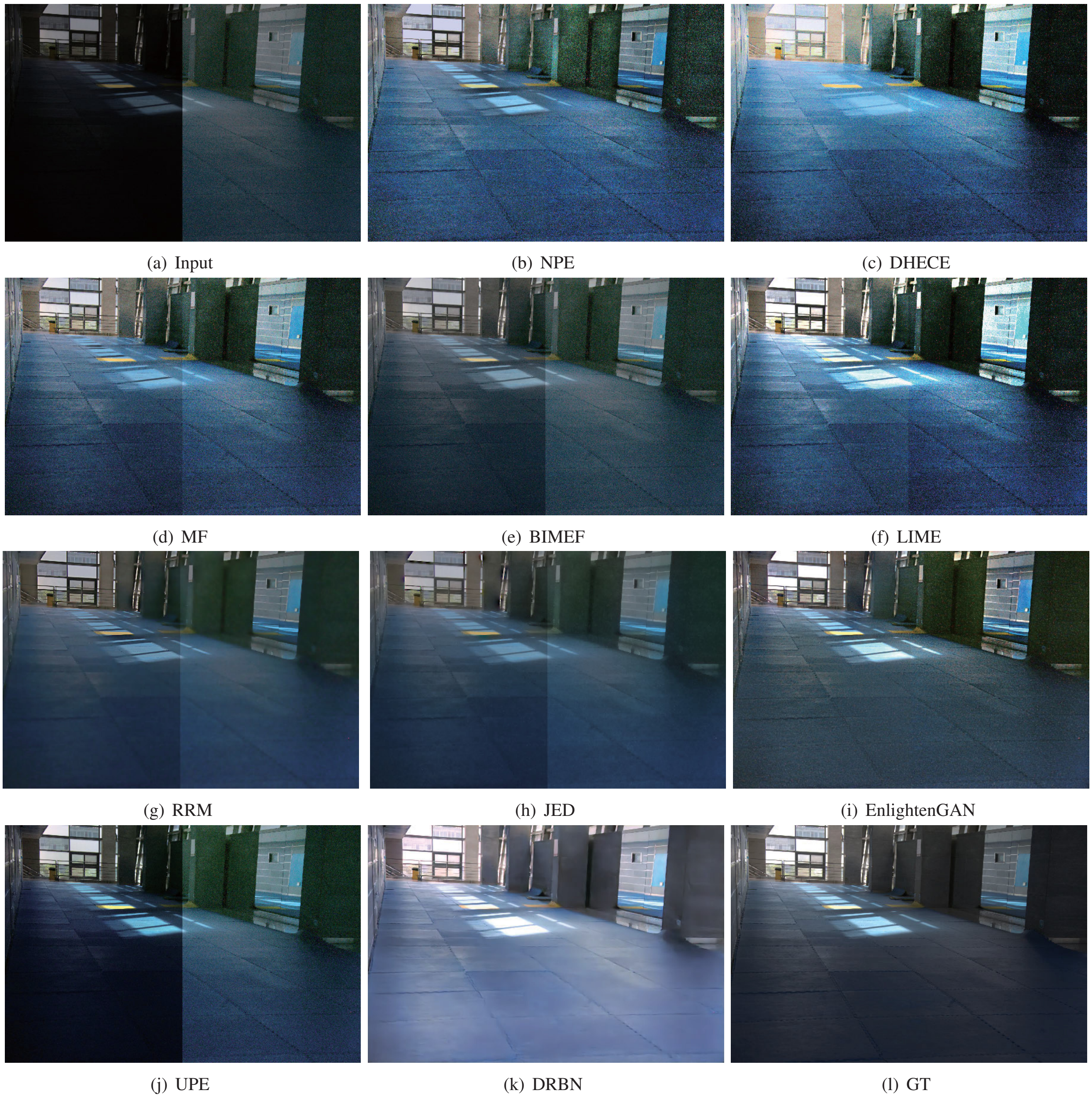


(a) Input (b) NPE (c) DHECE
(d) MF (e) BIMEF (f) LIME
(g) RRM (h) JED (i) EnlightenGAN
(j) UPE (k) DRBN (l) GT

Figure 3. The visual results of different methods on an input image from LOL dataset [13]. Left part: the original results. Right part: the results corrected by Gamma transformation for better visibility. Zooming-in the figure will provide a better look at the restoration quality.

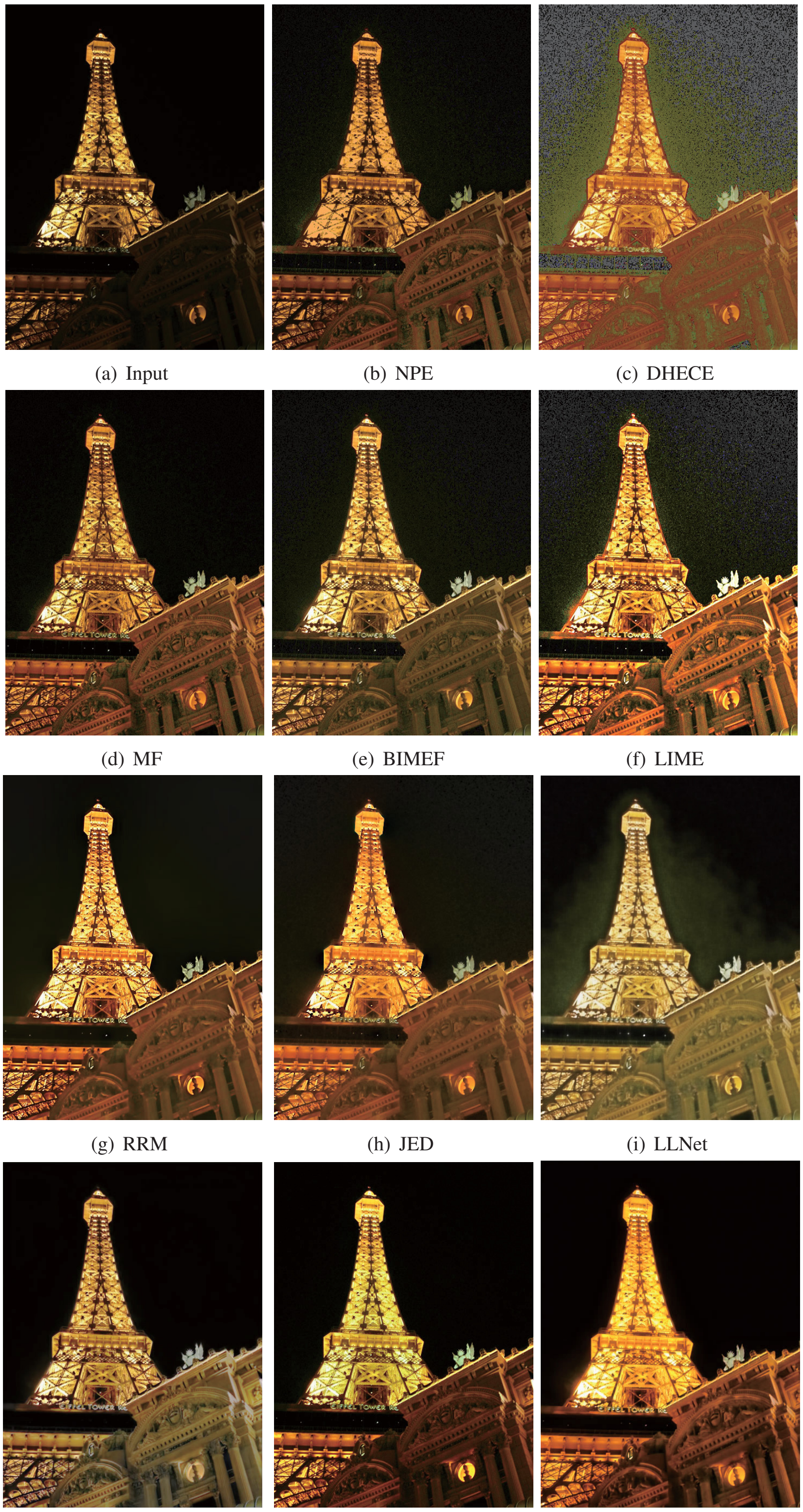
(a) Input (b) NPE (c) DHECE (d) MF (e) BIMEF (f) LIME (g) RRM (h) JED (i) EnlightenGAN (j) UPE (k) DRBN (l) GT

Figure 4. The visual results of different methods on an input image from LOL dataset [13]. Left part: the original results. Right part: the results corrected by Gamma transformation for better visibility. Zooming-in the figure will provide a better look at the restoration quality.



(a) Input (b) NPE (c) DHECE (d) MF (e) BIMEF (f) LIME (g) RRM (h) JED (i) EnlightenGAN (j) UPE (k) DRBN (l) GT

Figure 5. The visual results of different methods on an input image from LOL dataset [13]. Left part: the original results. Right part: the results corrected by Gamma transformation for better visibility. Zooming-in the figure will provide a better look at the restoration quality.



(a) Input (b) NPE (c) DHECE

(d) MF (e) BIMEF (f) LIME

(g) RRM (h) JED (i) LLNet

(j) KinD (k) UPE (l) DRBN

Figure 6. The visual results of different methods on an input image from DICM dataset [8]. Zooming-in the figure will provide a better look at the restoration quality.

(a) Input (b) NPE (c) DHECE (d) MF (e) BIMEF (f) LIME (g) RRM (h) JED (i) LLNet (j) KinD (k) UPE (l) DRBN

Figure 7. The visual results of different methods on an input image from NPE dataset [13]. Zooming-in the figure will provide a better look at the restoration quality.

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