# Self-Supervised Low-Light Image Enhancement Using Discrepant Untrained Network Priors (Supplementary Material)

### A. More Visual Comparisons with State-of-the-Art Methods

The compared methods include *(i) non-learning methods*: MSR [9], Dong *et al*. [2], NPE [16], PIE [3], SRIE [5], MF [4], BIMEF [21], JIEP [1], LIME [7], NPIE [15], RRM [10], STAR [18] and LR3M [13]; *(ii) models trained on paired data*: RetinexNet [17], DeepUPE [14], KinD [22], HybridNet [12], FIDE [19], and DRBN [20]; *(iii) models trained on an unorganized dataset*: EnlightenGAN (EnGAN for short) [8], ZeroDCE [6], and RUAS [11]; and *(iv) model trained without training data*: RetinexDIP [23]. The results of these methods are produced by their released codes with recommended parameter settings. See Fig. 12,14,15 for additional qualitative results on images captured under diverse low-light conditions. For low-light images with significant noise, our proposed method can restore comparatively vivid color and clear details while effectively suppressing noise; see *e.g*. Fig. 12 and Fig. 13. For low-light images with negligible noise, our proposed method shows comparable results with the state-of-the-arts; see *e.g*. Fig. 14 and Fig. 15.

### B. Retinex Decomposition Results

The Retinex decomposition results of different methods are visualized in Fig. 16. We include seven competitive Retinex-based methods for comparison. The comparison of enhancement results are shown in Fig. 17. Our proposed method can produce a smooth illumination map with sharp edges and a denoised reflectance map with rich details.

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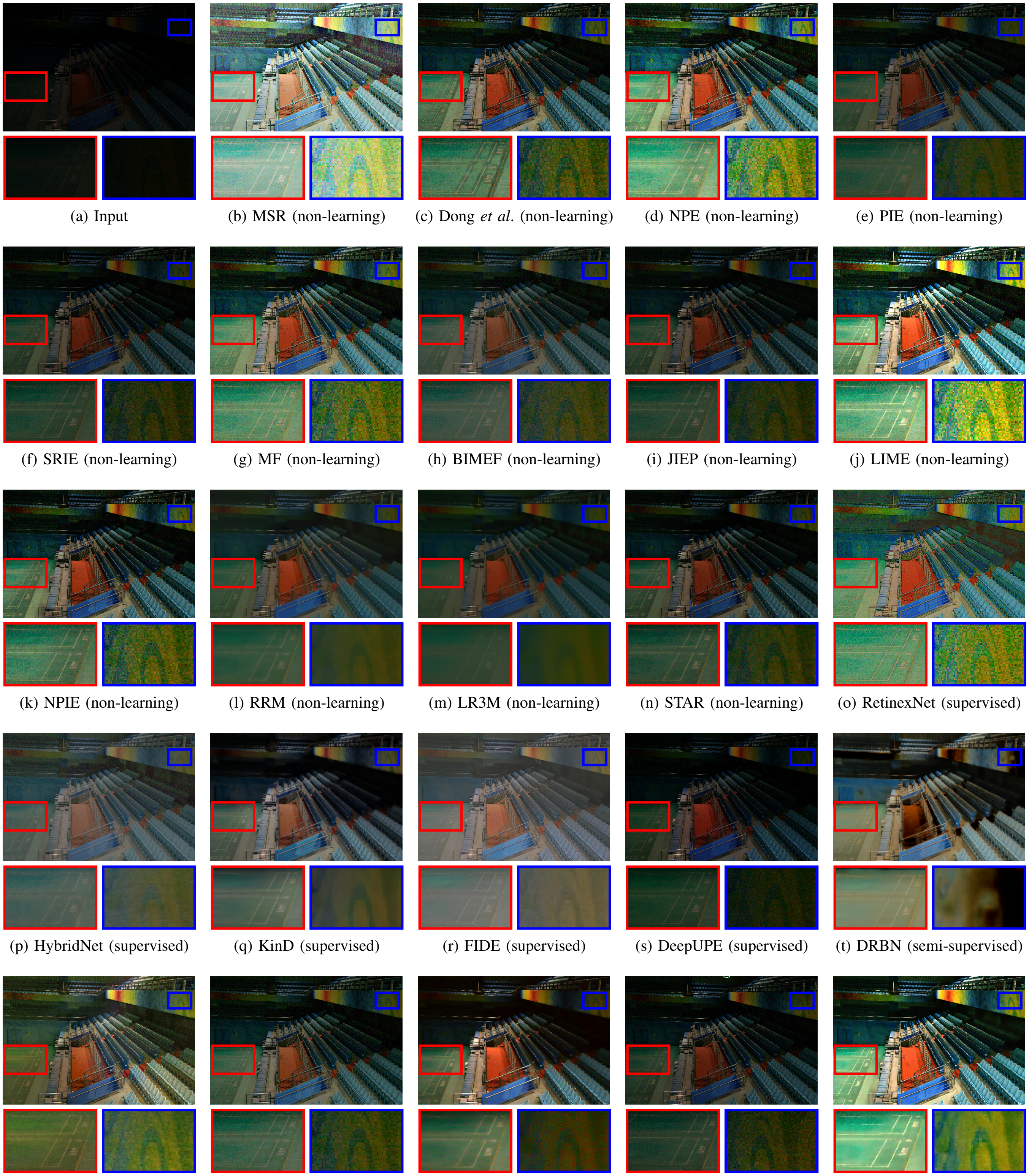


(a) Input (b) MSR (non-learning) (c) Dong *et al*. (non-learning) (d) NPE (non-learning) (e) PIE (non-learning)

(f) SRIE (non-learning) (g) MF (non-learning) (h) BIMEF (non-learning) (i) JIEP (non-learning) (j) LIME (non-learning)

(k) NPIE (non-learning) (l) RRM (non-learning) (m) LR3M (non-learning) (n) STAR (non-learning) (o) RetinexNet (supervised)

(p) HybridNet (supervised) (q) KinD (supervised) (r) FIDE (supervised) (s) DeepUPE (supervised) (t) DRBN (semi-supervised)

(u) EnGAN (unsupervised) (v) ZeroDCE (unsupervised) (w) RUAS (unsupervised) (x) RetinexDIP (dataset-free) (y) Ours (dataset-free)

Fig. 12: Visual comparison of enhancement results on an extreme low-light image. LIME can restore vivid color. However, the noise in the low-SNR regions is revealed in their results as shown in the red and blue boxes. Although KinD can suppress noise, the details are excessively blurred in some regions as shown in the blue boxes. In contrast, our proposed method is able to suppress noise in low-SNR regions while preserving color.

(a) Input (b) MSR (non-learning) (c) Dong *et al.* (non-learning) (d) NPE (non-learning) (e) PIE (non-learning)

(f) SRIE (non-learning) (g) MF (non-learning) (h) BIMEF (non-learning) (i) JIEP (non-learning) (j) LIME (non-learning)

(k) NPIE (non-learning) (l) RRM (non-learning) (m) LR3M (non-learning) (n) STAR (non-learning) (o) RetinexNet (supervised)

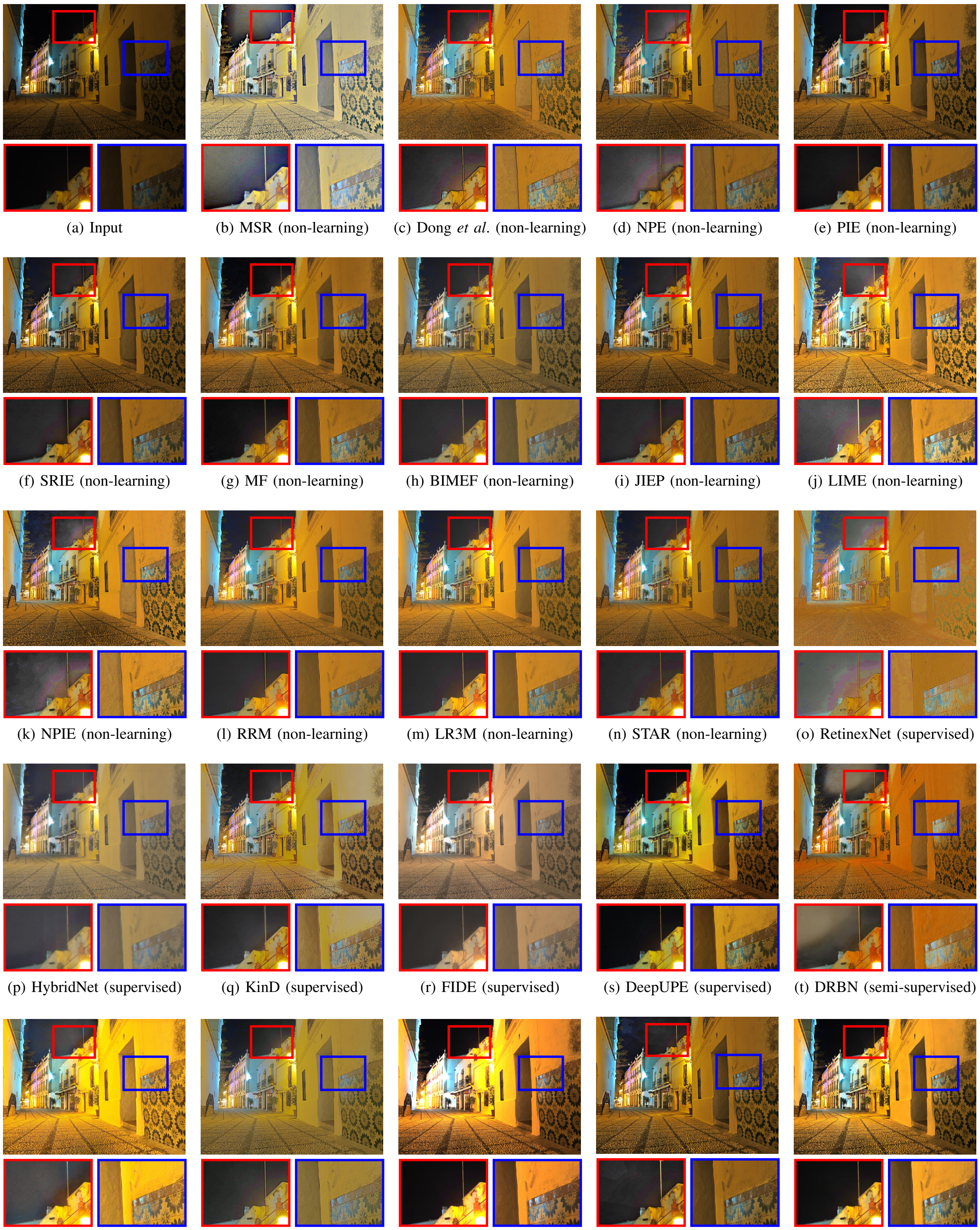
(p) HybridNet (supervised) (q) KinD (supervised) (r) FIDE (supervised) (s) DeepUPE (supervised) (t) DRBN (semi-supervised)

(u) EnGAN (unsupervised) (v) ZeroDCE (unsupervised) (w) RUAS (unsupervised) (x) RetinexDIP (dataset-free) (y) Ours (dataset-free)

Fig. 13: Visual comparison of enhancement results on an extreme low-light image. LIME can restore vivid color. However, due to the lack of an effective denoising mechanism, the noise in the low-SNR regions is revealed in their results as shown in the red and blue boxes. In contrast, our proposed method is able to suppress noise in low-SNR regions while preserving color.

(a) Input
(b) MSR (non-learning)
(c) Dong *et al*. (non-learning)
(d) NPE (non-learning)
(e) PIE (non-learning)
(f) SRIE (non-learning)
(g) MF (non-learning)
(h) BIMEF (non-learning)
(i) JIEP (non-learning)
(j) LIME (non-learning)
(k) NPIE (non-learning)
(l) RRM (non-learning)
(m) LR3M (non-learning)
(n) STAR (non-learning)
(o) RetinexNet (supervised)
(p) HybridNet (supervised)
(q) KinD (supervised)
(r) FIDE (supervised)
(s) DeepUPE (supervised)
(t) DRBN (semi-supervised)
(u) EnGAN (unsupervised)
(v) ZeroDCE (unsupervised)
(w) RUAS (unsupervised)
(x) RetinexDIP (dataset-free)
(y) Ours (dataset-free)

Fig. 14: Visual comparison of enhancement results on a low-light image, which shows that our proposed method can handle low-light images with negligible noise as well as the best methods. NPE, NPIE, EnGAN and our proposed method can well restore vivid color as well as fine details as shown in the red and blue boxes.



(a) Input (b) MSR (non-learning) (c) Dong *et al*. (non-learning) (d) NPE (non-learning) (e) PIE (non-learning)

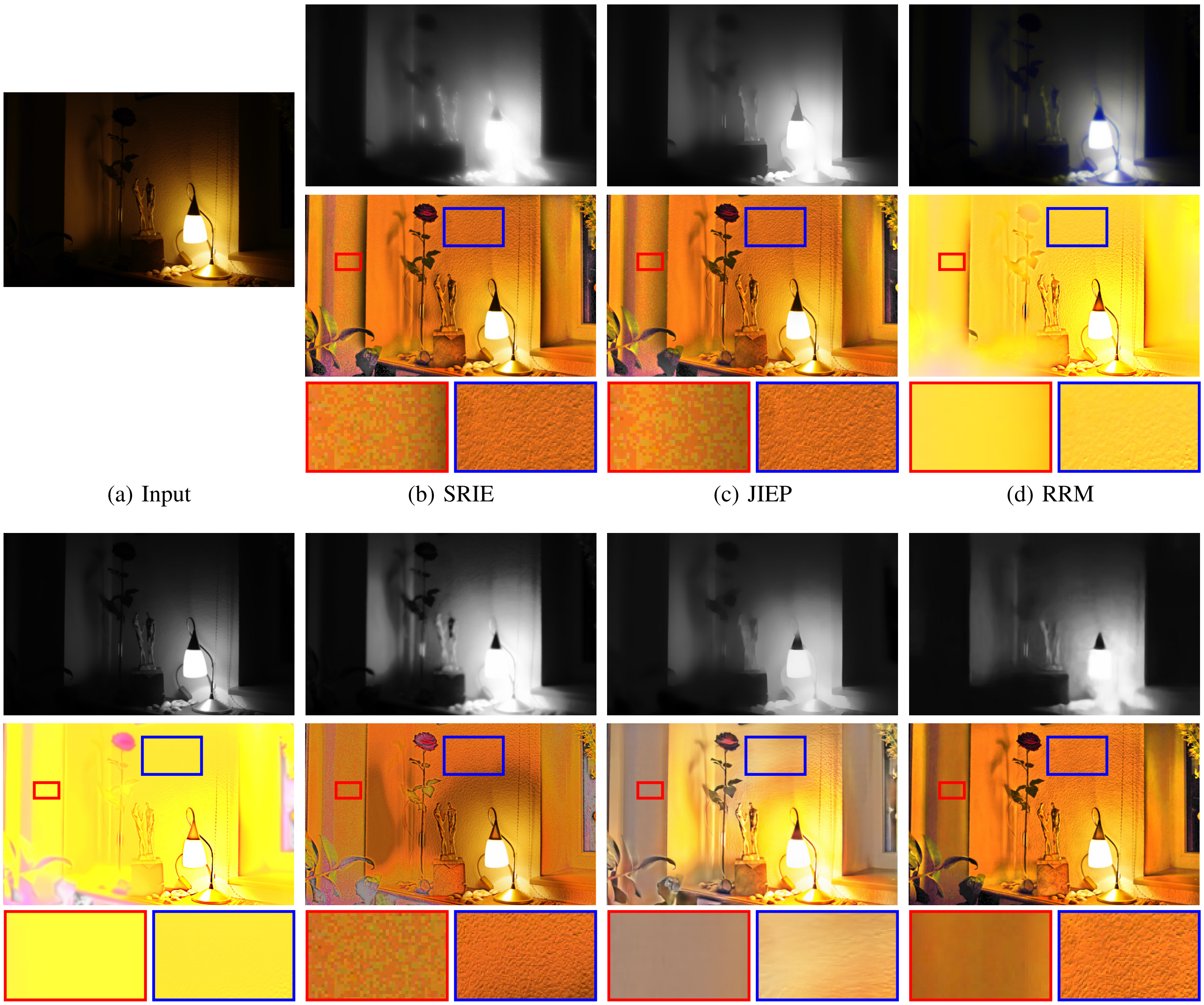
(f) SRIE (non-learning) (g) MF (non-learning) (h) BIMEF (non-learning) (i) JIEP (non-learning) (j) LIME (non-learning)

(k) NPIE (non-learning) (l) RRM (non-learning) (m) LR3M (non-learning) (n) STAR (non-learning) (o) RetinexNet (supervised)

(p) HybridNet (supervised) (q) KinD (supervised) (r) FIDE (supervised) (s) DeepUPE (supervised) (t) DRBN (semi-supervised)

(u) EnGAN (unsupervised) (v) ZeroDCE (unsupervised) (w) RUAS (unsupervised) (x) RetinexDIP (dataset-free) (y) Ours (dataset-free)

Fig. 15: Visual comparison of enhancement results on a moderate low-light image, which shows that our proposed method can handle moderate low-light images as well as the best methods. Many methods that can well restore global illumination, *e.g*., LIME, NPIE, EnGAN produce severe artifacts in the sky as shown in the red boxes. Moreover, the walls with paintings in the bottom-right are wrongly assigned light color by them, which should be dark as can be seen in the (a) input image. In contrast, RUAS, DeepUPE and our proposed method can well restore global illumination as well as local color and details.



(a) Input (b) SRIE (c) JIEP (d) RRM

(e) LR3M (f) RetinexNet (g) KinD (h) Ours

Fig. 16: Visual comparison of Retinex decomposition results. (b)-(h): Top: illumination. Bottom: reflectance. For SRIE and JIEP, the edges (*e.g.*, the edges of the wall on the right) in illumination are over-smoothed. For JIEP, SRIE and RetinexNet, a noticeable amount of noise is presented in reflectance (*e.g.*, red boxes). For RRM, LR3M and KinD, the output reflectance looks blurry with some details lost (*e.g.*, blue boxes). In comparison, our proposed method produced a smooth illumination map with sharp edges, as well as a clean reflectance map with rich details.

(a) RetinexNet (b) KinD (c) RUAS (d) RetinexDIP (e) Ours

Fig. 17: Visual comparison between our proposed method and several deep Retinex methods. RetinexNet produces results with vivid color and pleasing appearances in most cases. However, it also produces severe artifacts and cartoonish effects. RUAS produces some over-exposed regions. Comparatively, KinD, RetinexDIP, and our proposed method can obtain more natural illumination and details.