Unsupervised Night Image Enhancement: When Layer Decomposition Meets Light-Effects Suppression
(Supplementary Material)

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In this supplementary material, we provide:

1. More Experimental Results
   1-1) Light Effects Suppression Results on
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1 More Experimental Results

1.1 Light Effects Suppression Results

Figs. 1 to 4 show results on real night images in comparison with the baselines. Fig 5 shows results on real night images in Dark Zurich dataset [33]. We compare our method with: light effects suppression methods: Sharma [34], and also the image enhancement methods: EnlightenGAN [15], Afifi et al. [1], ZeroDCE++ [20], etc. night dehazing methods: Yan et al. [39], Zhang et al. [48], Li et al. [23].

Our results are robust in suppressing light effects, enhancing the dark regions, and better preserving the background information than baselines.

Fig. 1. Comparing light-effects suppression and dark regions enhancement results on a real night image.
Fig. 2. Comparing light-effects suppression and dark regions enhancement results on a real night image.
Fig. 3. Comparing light-effects suppression and dark regions enhancement results on a real night image.
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Fig. 4. Comparing light-effects suppression and dark regions enhancement results on a real night image.
Fig. 5. Comparing light-effects suppression and dark regions enhancement results on a real night image from Dark Zurich [33] dataset. The name of the input night image is GOPR0364_frame_000939_rgb_anon.
1.2 Low-light Enhancement Results

Fig. 6 and Fig. 7 show visual results on the LOL-test dataset, the quantitative results are provided in Table 1. Figs. 8 to 11 show visual results on LOL-Real dataset, the quantitative results are provided in Table 2. Fig. 12 shows our pipeline can boost the brightness of low-light images that have no light effects.

![Image of comparison results](image)

**Fig. 6.** Comparing low light enhancement results on the LOL-test dataset [5].
Fig. 7. Comparing low light enhancement results on the LOL-test dataset [5].
Fig. 8. Comparing low light enhancement results on the LOL-Real [42] dataset.
**Fig. 9.** Comparing low light enhancement results on the LOL-Real [42] dataset.
Fig. 10. Comparing low light enhancement results on the LOL-Real [42] dataset.
Fig. 11. Comparing low light enhancement results on the LOL-Real [42] dataset.
Table 1. Quantitative comparisons on images from LOL-test dataset [5]. Top two results are in red and blue respectively. Noted our method is unsupervised.

| Method       | LOL-test | Learning |
|--------------|----------|----------|
|              | MSE      | PSNR     | SSIM    | LPIPS   |
| input        | 12.615   | 7.777    | 0.181   | 0.560   |
| LIME [14]    | 16.72    | 0.58     | -       | -       |
| MF [8]       | 16.76    | 0.56     | -       | -       |
| RRM [22]     | 18.79    | 0.64     | -       | -       |
| SRIE [9]     | 11.86    | 0.59     | -       | -       |
| MR [16]      | 13.17    | 0.48     | -       | -       |
| NPE [37]     | 16.97    | 0.59     | -       | -       |

Table 2. Quantitative comparisons on the LOL-Real dataset [42].

| Learning | Method       | Output | NA | Opti | Opti | Opti | Opti | Opti | Opti | Opti | Opti | Opti | Opti | Opti | Opti |
|----------|--------------|--------|----|------|------|------|------|------|------|------|------|------|------|------|------|
|          | Input        | BPDHE [13] | CRM [46] | DHECE [30] | Dong [7] | EFF [45] | CLAHE [56] | LIME [14] | MF [8] |
|          | PSNR↑       | 0.18   | 0.42  | 0.66  | 0.44  | 0.52  | 0.65  | 0.37  | 0.53  | 0.55  |

| Learning | Method       | Output | Opti | Opti | Opti | Opti | Opti | Opti | Opti | Opti | Opti | Opti | Opti | Opti | Opti |
|----------|--------------|--------|------|------|------|------|------|------|------|------|------|------|------|------|------|
|          | Input        | JED [32] | CRM [46] | DHECE [30] | Dong [7] | EFF [45] | CLAHE [56] | LIME [14] | MF [8] |
|          | PSNR↑       | 11.67  | 17.35 | 17.34 | 17.34 | 11.43 | 12.67 | 14.85 | 20.54 | 15.35 |
|          | SSIM↑       | 0.42   | 0.66  | 0.68  | 0.68  | 0.36  | 0.41  | 0.56  | 0.78  | 0.52  |

| Learning | Method       | Output | Opti | Opti | Opti | Opti | Opti | Opti | Opti | Opti | Opti | Opti | Opti | Opti | Opti |
|----------|--------------|--------|------|------|------|------|------|------|------|------|------|------|------|------|------|
|          | Input        | LLNet [26] | RN [5] | DUPE [36] | SICE [3] | Afifi [1] | DRBN [41] | RG [15] | Sharma [34] | Ours |
|          | PSNR↑       | 17.56  | 15.47 | 13.27 | 19.40 | 16.38 | 19.66 | 18.23 | 18.34 | 25.53 |
|          | SSIM↑       | 0.54   | 0.56  | 0.45  | 0.69  | 0.53  | 0.76  | 0.61  | 0.64  | 0.88  |
Fig. 12. The overall architecture of our proposed method for low-light enhancement. Besides night light-effects suppression, our method can boost the brightness of low-light images that have no light-effects, by simply setting the light-effects layer to $G_0$, a dummy all zero map, which has no light-effects. For the layer decomposition, the image-layer model $I = R \odot L + G_0$, which enhances illumination in dark regions. For the light-effects suppression network, we input unpaired low-light $(G_0, J_{init})$ and normal-light images $(G_0, J_{ref})$ to the network. The network learns to enhance the illumination from unpaired data.

2 Experiments and Training Details

2.1 Real Night Data

We collect a small set of light effects nighttime images where we can have clean reference counterparts. Fig. 13 shows our qualitative evaluations on real data.

We use a Manfrotto Lykos bi-color LED light and set our camera/phone to be stationary. All the images are taken from Sonyα7R III digital camera and iPhone 12. For diversity in our evaluation dataset, we collect nighttime images with varying illumination, background scenes and light effects intensity. The collection procedure is as follows:

1. We fix the camera/phone position and the source of the light effect (e.g., our LED light).
2. We turn on the light effects source and record an image (the input shown in Fig. 13a).
3. We reduce the intensity of the light effects source and record another image (the low-light light-effects-free image shown in Fig. 13b).
Fig. 13. Qualitative comparisons with the state-of-the-art methods on real night dataset Real-light-effects.
2.2 Synthetic Night Data

Inspired by [29, 31], we evaluate on a small set of images with light effects (Syn-light-effects) shown in Fig. 14 using the traditional light-effects model with optical thickness $T = 1.2$, scattering parameter $q = 0.55$.

Fig. 14. Qualitative comparisons with the state-of-the-art methods on paired synthetic night data Syn-light-effects.
We also train and test our method on synthetic GTA5 night images (provided by [39]) simulated using [6]. For our unpaired training, we use light-effects and light-effects-free synthetic night images. We use 200 synthetic paired light-effects/light-effects-free night images for our evaluation.

![Image of Qualitative Comparisons]

**Fig. 15.** Qualitative comparisons with the state-of-the-art methods on synthetic night data GTA5 [6].
2.3 Gradient Exclusion Loss

The definition of the gradient exclusion loss follows [10, 50] and is computed by taking the product of normalized gradient fields of $G$ and $J_{init}$:

$$L_{excl} = \sum_{n=1}^{3} \| \tanh(\lambda_{G_{init}} |\nabla G_{\downarrow n}|) \circ \tanh(\lambda_{J_{init}} |\nabla J_{\downarrow n}|) \|_{F},$$ (1)

where $\| \cdot \|_F$ is the Frobenius norm, $G_{\downarrow n}$ and $J_{\downarrow n, \text{init}}$ represent $G$ and $J_{\text{init}}$ down-sampled by a factor of $2^{n-1}$ using bilinear interpolation respectively, and the parameters $\lambda_{G_{\downarrow n}} = \sqrt{\|\nabla J_{\downarrow \text{init}}\|_F / \|\nabla G_{\downarrow n}\|_F}$ and $\lambda_{J_{\downarrow \text{init}}} = \sqrt{\|\nabla G_{\downarrow n}\|_F / \|\nabla J_{\downarrow \text{init}}\|_F}$ are normalization factors.

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**Fig. 16.** The gradient histogram of the light-effects layer $G$ has a short tail distribution [23]. Light-effects layers have few large gradients.
2.4 Network Architecture

For the light-effects suppression network $\phi_{\text{gen}}$, we use two convolution layers with a stride size of two for down-sampling in the encoder, four residual blocks with adaptive layer-instance normalization [17] and two up-sampling convolution layers in the decoder. Note that, we add residual connection in the generator network. The channel dimensions are from 3 to 64, 128, 256 for the downsampling encoder, followed by a few layers that have the feature channel dimensionalities of 256, 256, 256, 256, before getting into the upsampling decoder with the channel dimensionalities of 128, 64, 3.

To make the attention feature map focus on the light-effects regions, we connect the auxiliary classifier $\Gamma_{\text{gen}}$ from the encoder in the generator $\phi_{\text{gen}}$. The attention map comes from the auxiliary classifier $\Gamma_{\text{gen}}$ using CAM (class activation map) [54] to learn the weights.

We use PatchGAN [14] architectures with six convolution layers for the discriminators. The global discriminator processes an entire image of resolution $512 \times 512$ while the local discriminator processes small patches of resolution $70 \times 70$ cropped randomly from the image. We adopt Adam [18] as the optimization solver.

2.5 Daytime Flare Removal

The goal of the paper is to obtain a clear background scene in a night image, independent from light-effects. Importantly, our method is learning-based, as shown in Fig.2, where our first layer decomposition module tries to separate the layers; and second, our translation network learns from the data to suppress light-effects that can degrade visibility.

While our framework is designed for night image enhancement, the unsupervised light-effects suppression network can also work for daytime flare removal since it learns from the unpaired flare/flare-free data shown in Fig. 17. Using constraints specific to daytime to handle remaining problems will be part of our future work.

![Fig. 17. Our daytime flare removal results on the flare dataset [38].](image-url)
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