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**
     - 1-1-1) real night images (Figs. 1 to 4)
     - 1-1-2) Dark Zurich dataset (Fig. 5)
   - 1-2) **Low-light Enhancement Results on**
     - 1-2-1) LOL dataset (Fig. 6 and Fig. 7, Table 1)
     - 1-2-2) LOL-Real dataset (Figs. 8 to 11, Table 2)
     - 1-2-3) low-light enhancement pipeline (Fig. 12)
2. **Experiments and Training Details**
   - 2-1) **Real Night Data** (Fig. 13)
   - 2-2) **Synthetic Night Data** (Fig. 14 and Fig. 15)
   - 2-3) **Gradient Exclusion Loss** (Fig. 16)
   - 2-4) **Network Architecture**
   - 2-5) **Daytime Flare Removal** (Fig. 17)

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 show 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.

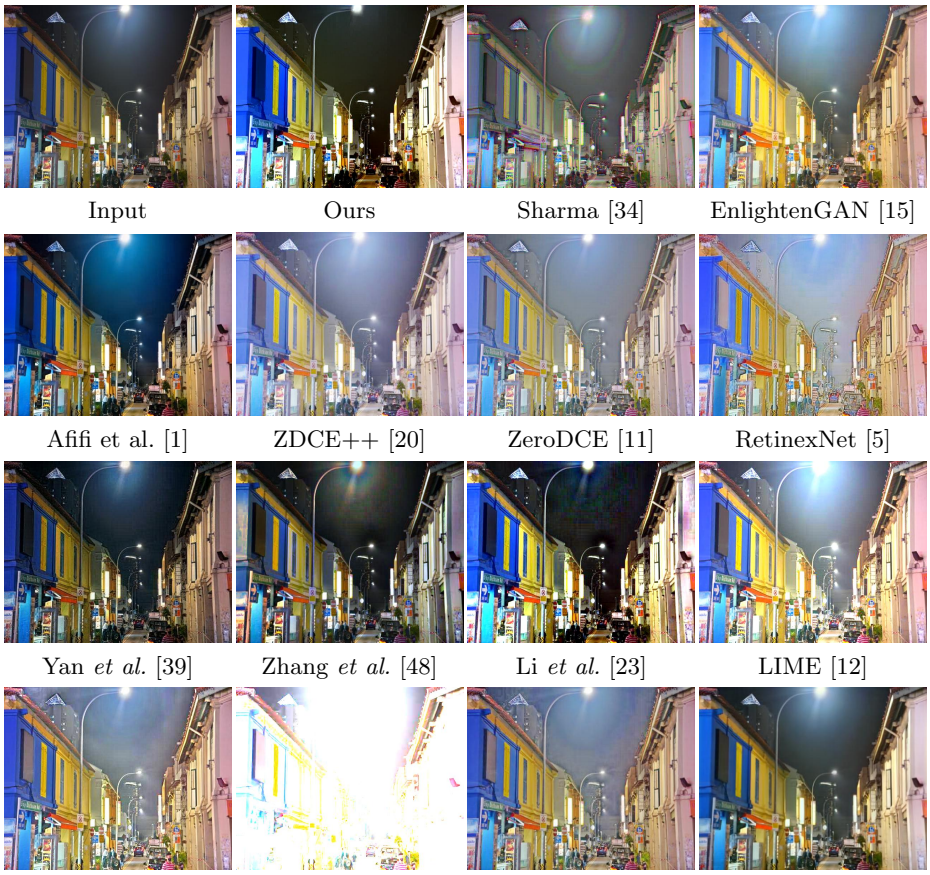

Fig. 2. Comparing light-effects suppression and dark regions enhancement results on a real night image.

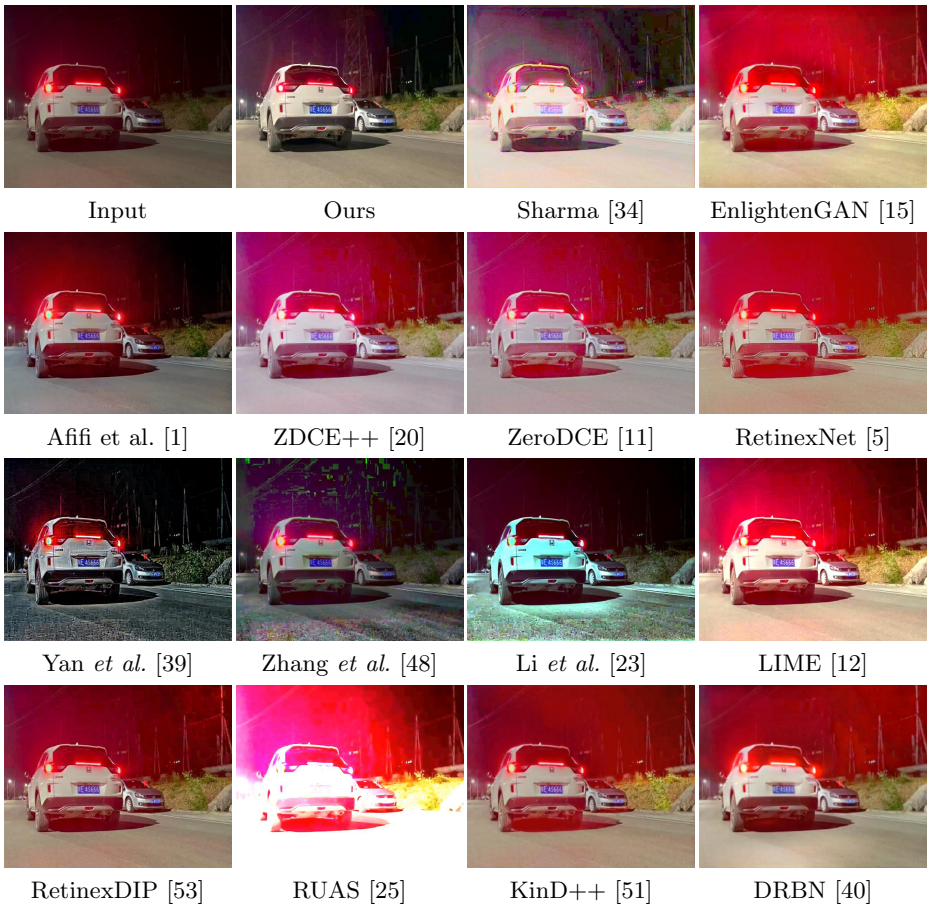

Fig. 3. Comparing light-effects suppression and dark regions enhancement results on a real night image.

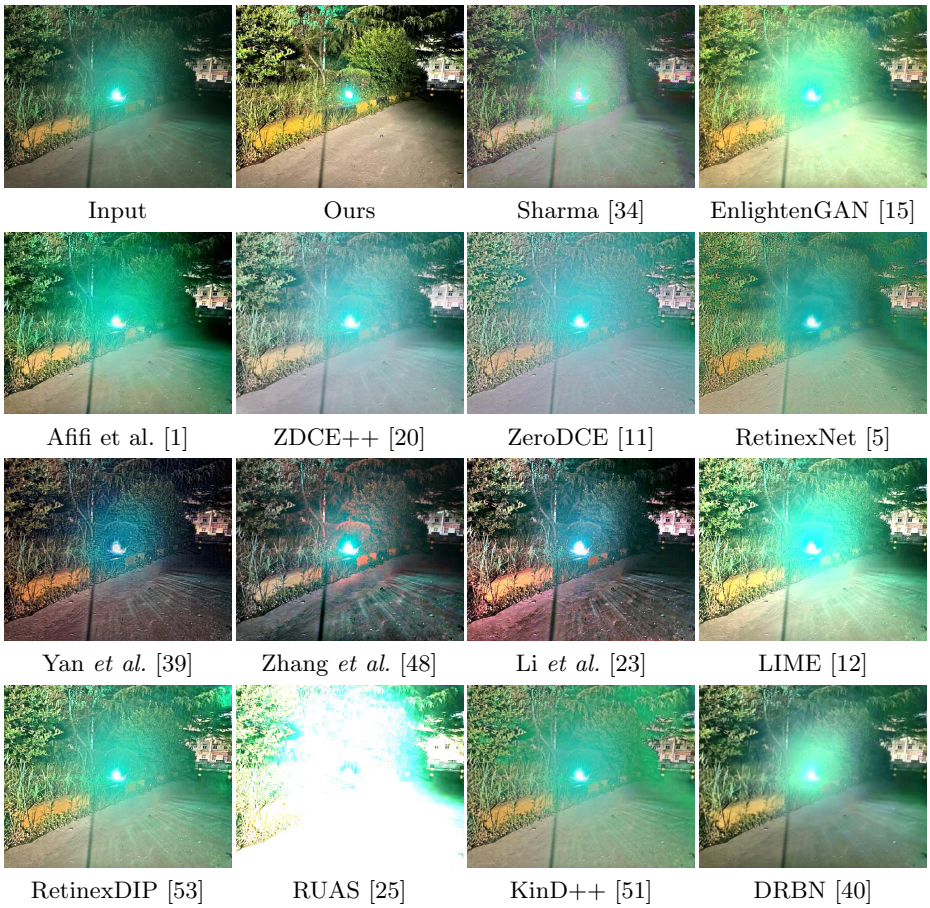

Fig. 4. Comparing light-effects suppression and dark regions enhancement results on a real night image.

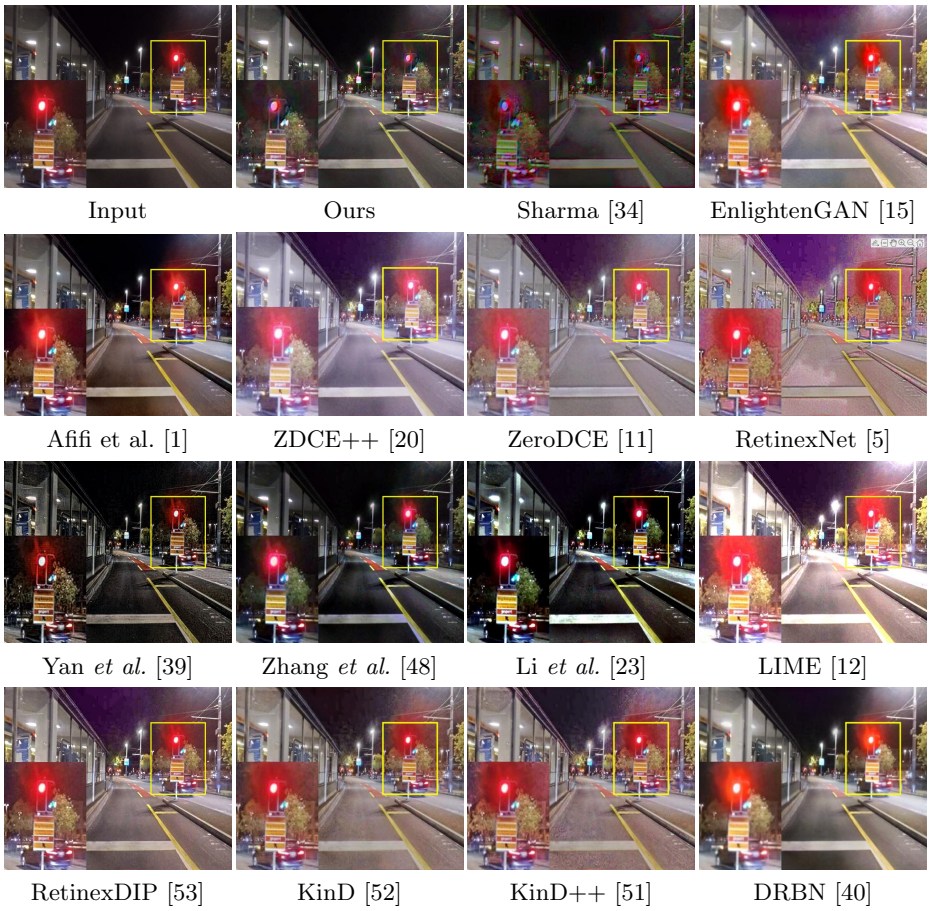

Fig. 5. Comparing light-effects suppression and dark regions enhancement results on a real night image from Dark Zurich [33] dataset. The name of the input night image is `GOPR0364_frame_000939_rgb_anon`.

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.

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.

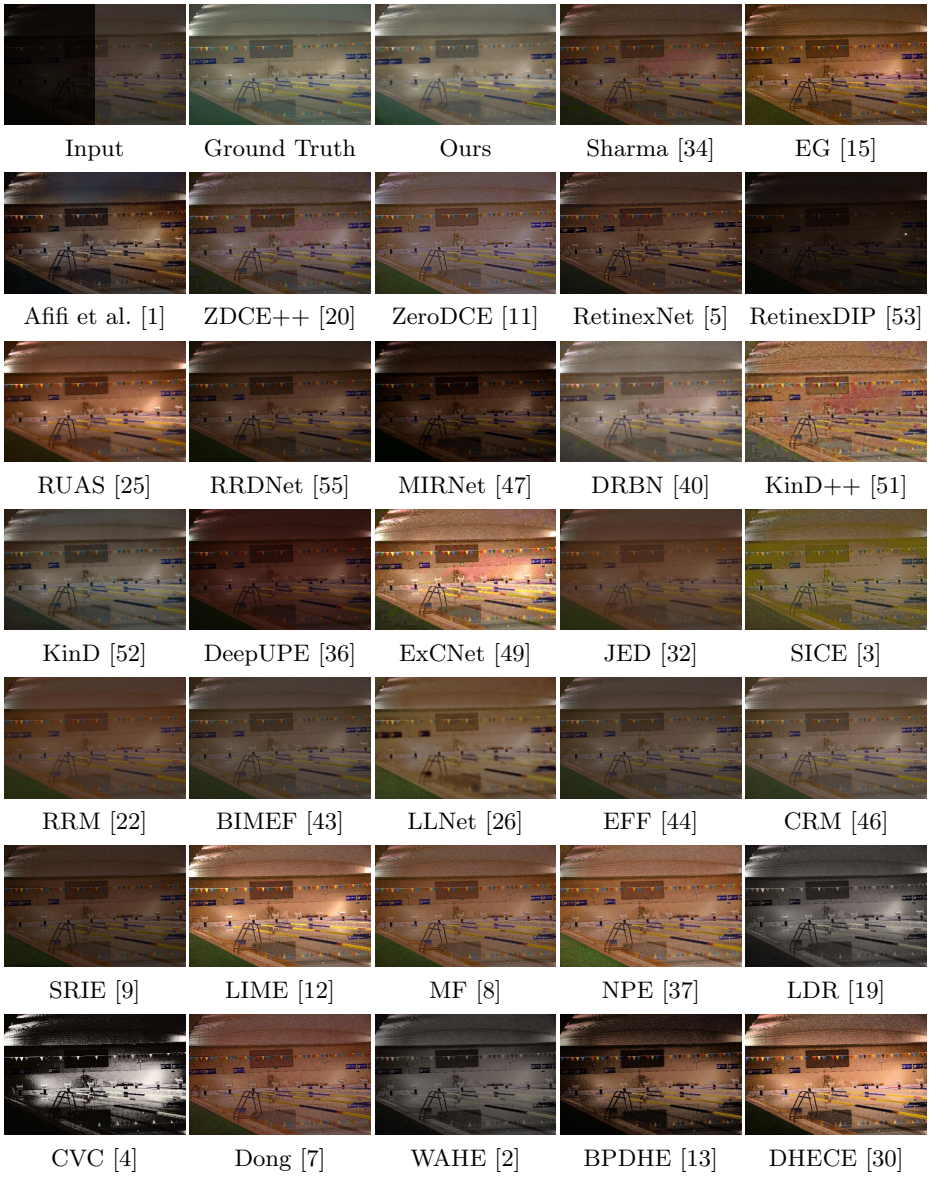

Fig. 11. Comparing low light enhancement results on the LOL-Real [42] dataset.

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.

Learning	Method	LOL-test			
		MSE ↓	PSNR ↑	SSIM ↑	LPIPS ↓
	input	12.613	7.773	0.181	0.560
Opt	Dong [7]	-	16.72	0.58	-
	LIME [12]	-	16.76	0.56	-
	MF [8]	-	18.79	0.64	-
	RRM [22]	-	13.88	0.66	-
	SRIE [9]	-	11.86	0.50	-
	MR [16]	-	13.17	0.48	-
	NPE [37]	-	16.97	0.59	-
SL	LLNet [26]	1.290	17.959	0.713	0.360
	LightenNet [21]	7.614	10.301	0.402	0.394
	RetinexNet [5]	1.651	16.774	0.462	0.474
	MBLLEN [28]	1.444	17.902	0.715	0.247
	KinD [52]	1.431	17.648	0.779	0.175
	KinD++ [51]	1.298	17.752	0.760	0.198
	TBEFN [27]	1.764	17.351	0.786	0.210
	DSLR [24]	3.536	15.050	0.597	0.337
	Afifi [1]	4.520	15.300	0.560	0.392
	RUAS [25]	3.920	18.230	0.720	0.350
ZSL	ExCNet [49]	2.292	15.783	0.515	0.373
	ZeroDCE [11]	3.282	14.861	0.589	0.335
	RRDNet [55]	6.313	11.392	0.468	0.361
SSL	DRBN [40]	2.359	15.125	0.472	0.316
UL	EnlightenGAN [15]	1.998	17.483	0.677	0.322
SSL	Sharma [34]	3.350	16.880	0.670	0.315
UL	Ours	1.070	21.521	0.763	0.235

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

Learning	NA	Opti	Opti	Opti	Opti	Opti	Opti	Opti	Opti
Method	Input	BPDHE [13]	CRM [46]	DHECE [30]	Dong [7]	EFF [45]	CLAHE [56]	LIME [12]	MF [8]
PSNR↑	9.72	13.84	19.65	14.64	17.26	17.85	13.13	14.07	18.73
SSIM↑	0.18	0.42	0.66	0.44	0.52	0.65	0.37	0.53	0.55
Learning	Opti	Opti	Opti	Opti	ZSL	ZSL	ZSL	ZSL	SL
Method	MR [16]	JED [32]	RRM [22]	SRIE [9]	RDIP [53]	MIRNet [47]	RRDNet [55]	ZD [11]	RUAS [25]
PSNR↑	11.67	17.33	17.34	17.34	11.43	12.67	14.85	20.54	15.33
SSIM↑	0.42	0.66	0.68	0.68	0.36	0.41	0.56	0.78	0.52
Learning	SL	SL	SL	SL	SL	SSL	UL	SSL	UL
Method	LLNet [26]	RN [5]	DUPE [36]	SICE [3]	Afifi [1]	DRBN [41]	EG [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**

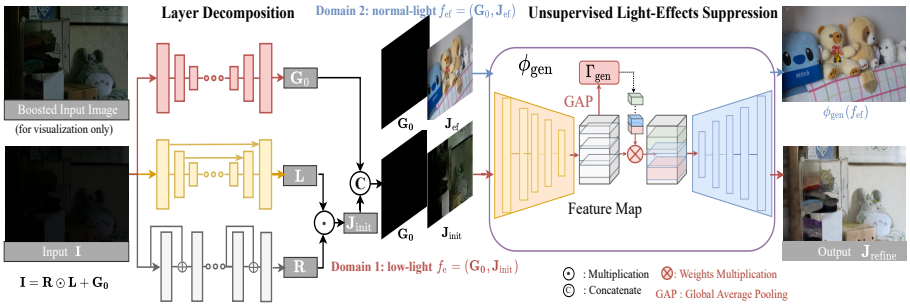

Fig. 12. The overall architecture of our proposed method for low-light enhancement. Besides night light-effects suppression, our method can boost the brightness of low-light images that have no light-effects, by simply setting the light-effects layer to $\mathbf{G}_0$, a dummy all zero map, which has no light-effects. For the layer decomposition, the image-layer model $\mathbf{I} = \mathbf{R} \odot \mathbf{L} + \mathbf{G}_0$, which enhance illumination in dark regions. For the light-effects suppression network, we input unpaired low-light $(\mathbf{G}_0, \mathbf{J}_{\text{init}})$ and normal-light images $(\mathbf{G}_0, \mathbf{J}_{\text{ef}})$ 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).

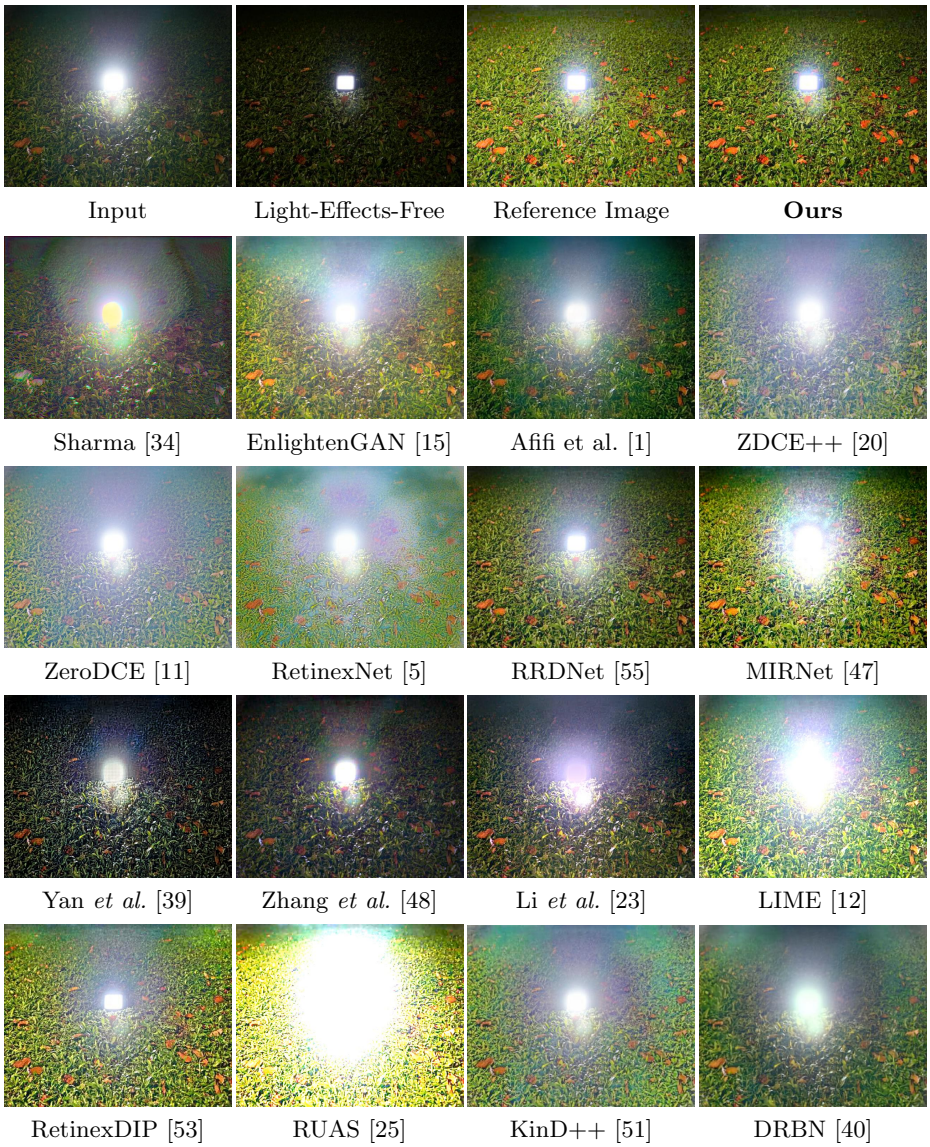

Fig. 13. Qualitative comparisons with the state-of-the-art methods on real night dataset Real-light-effects.

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 $q = 0.55$.

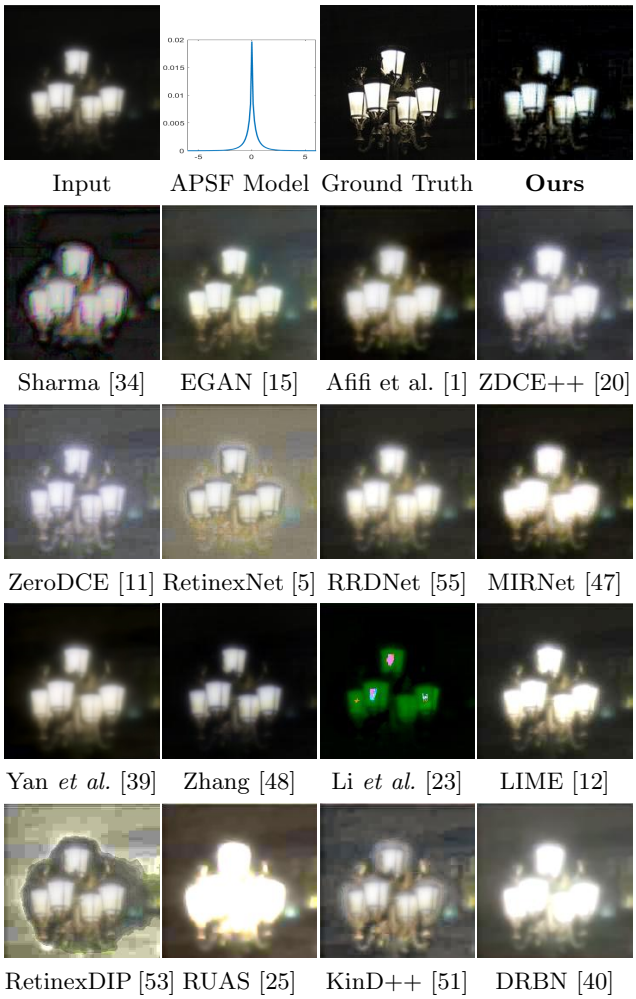

Fig. 14. Qualitative comparisons with the state-of-the-art methods on paired synthetic night data Syn-light-effects.

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.

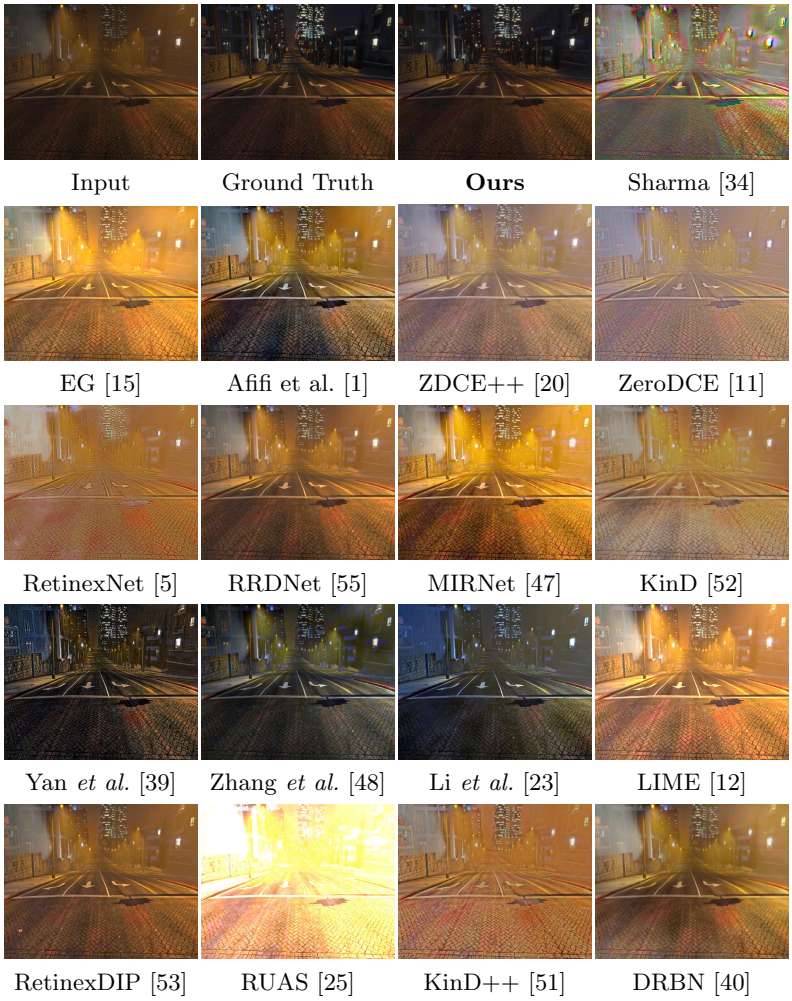

Fig. 15. Qualitative comparisons with the state-of-the-art methods on synthetic night data GTA5 [6].

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 $\mathbf{G}$ and $\mathbf{J}_{\text{init}}$:

$$\mathcal{L}_{\text{excl}} = \sum_{n=1}^{3} \left\| \tanh(\lambda_{\mathbf{G}^{\downarrow n}} |\nabla \mathbf{G}^{\downarrow n}|) \circ \tanh(\lambda_{\mathbf{J}_{\text{init}}^{\downarrow n}} |\nabla \mathbf{J}_{\text{init}}^{\downarrow n}|) \right\|_F, \tag{1}$$

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

Input Light-Effects Layer $\mathbf{G}$ Gradient Histogram of $\mathbf{G}$

Fig. 16. The gradient histogram of the light-effects layer $\mathbf{G}$ has a short tail distribution [23]. Light-effects layers have few large gradients.

2.4 Network Architecture

For the light-effects suppression network ϕ_{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 Γ_{gen} from the encoder in the generator ϕ_{gen}. The attention map comes from the auxiliary classifier Γ_{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 512×512 while the local discriminator processes small patches of resolution 70×70 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.

Input | Our | Sharma [34] | Wu et al. [38] | Ground Truth

Fig. 17. Our daytime flare removal results on the flare dataset [38].

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