



Unsupervised Night Image Enhancement: When Layer Decomposition Meets Light-Effects Suppression

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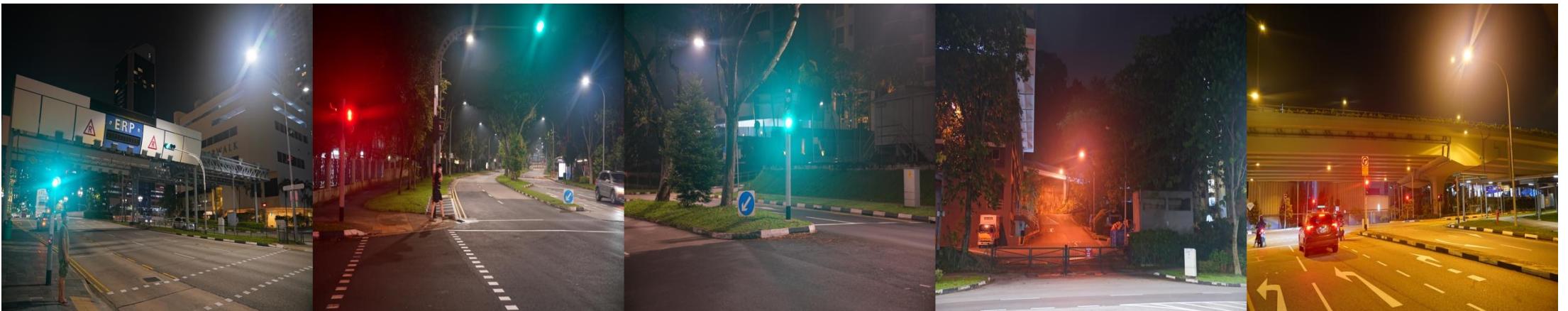
Problem & Motivation & Challenge

Night Image Problems

- Low Light:



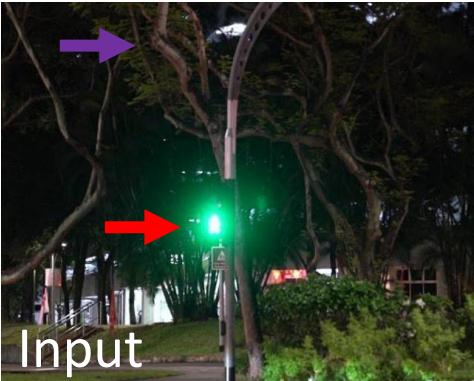
- Light-Effects/Glare/Floodlight:



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Motivation

- Existing low-light enhancement methods:



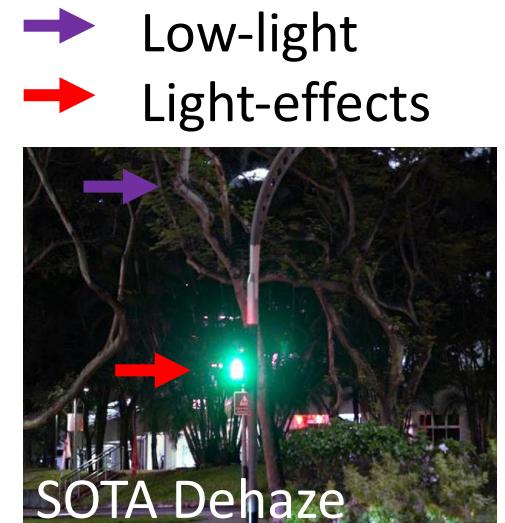
✓ Enhance low-light



✗ Over-enhance light-effects



SOTA Enhance



SOTA Dehaze

- Existing night dehazing methods:



✗ Enhance low-light

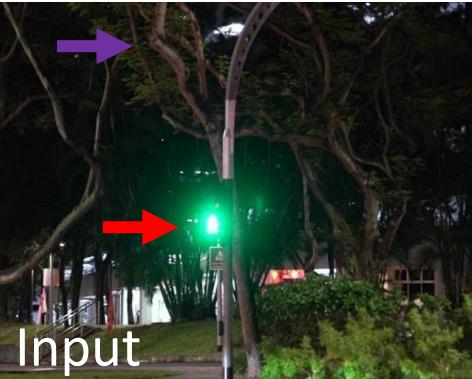


✗ Suppress light-effects

Main task: ✓ Boost low-light, at the same time, ✓ suppress light-effects.

Challenge

➤ Our:



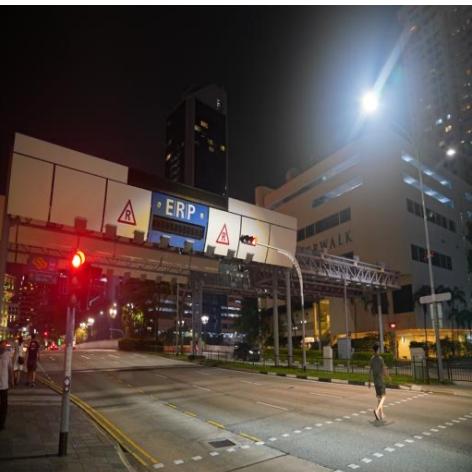
✓ Enhance low-light



✓ Suppress light-effects



→ Low-light
→ Light-effects



Challenge:

- Lack of **paired** training data
- Rendering is challenging

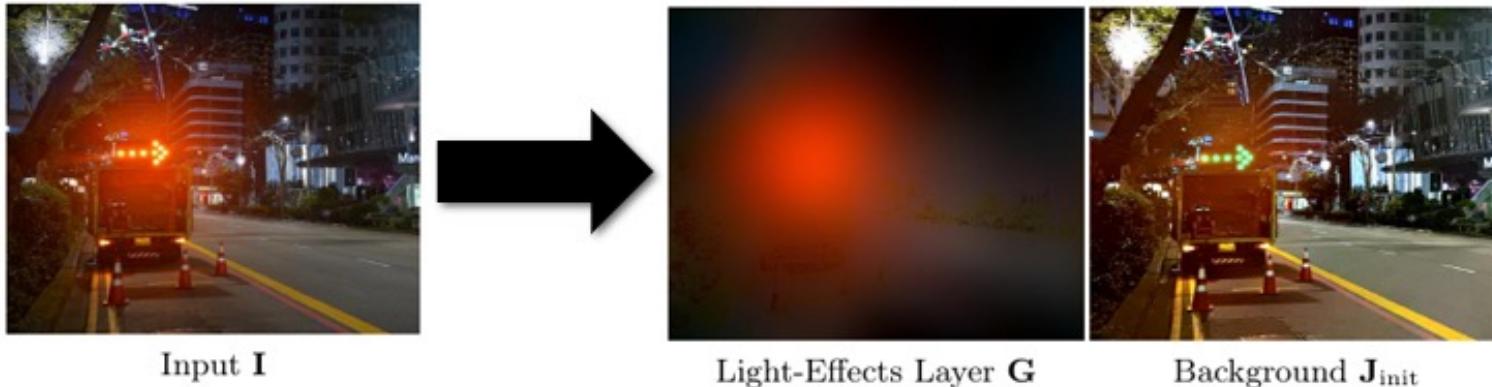
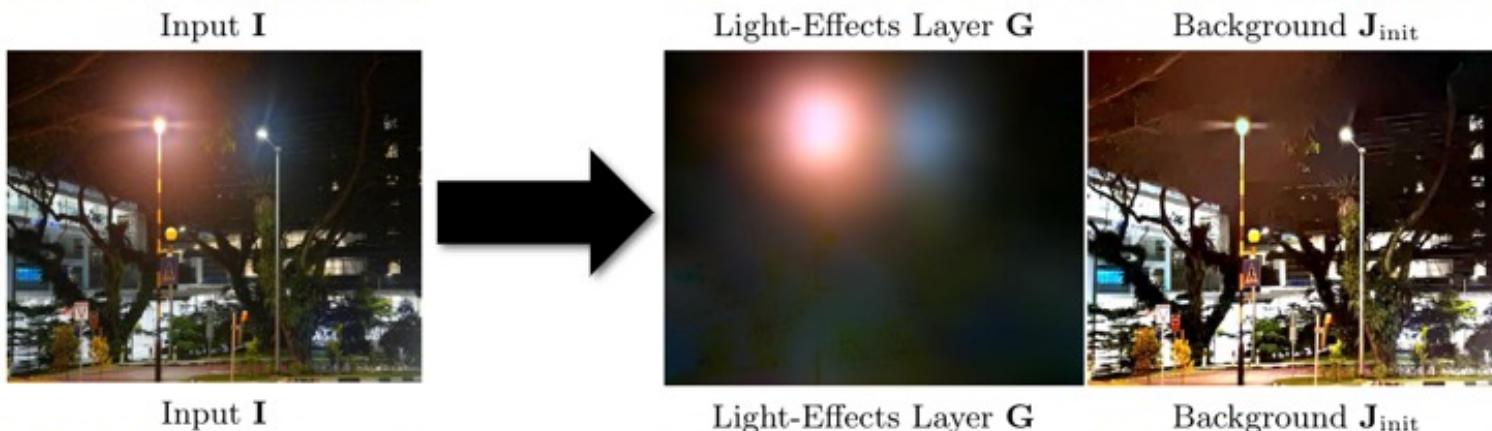
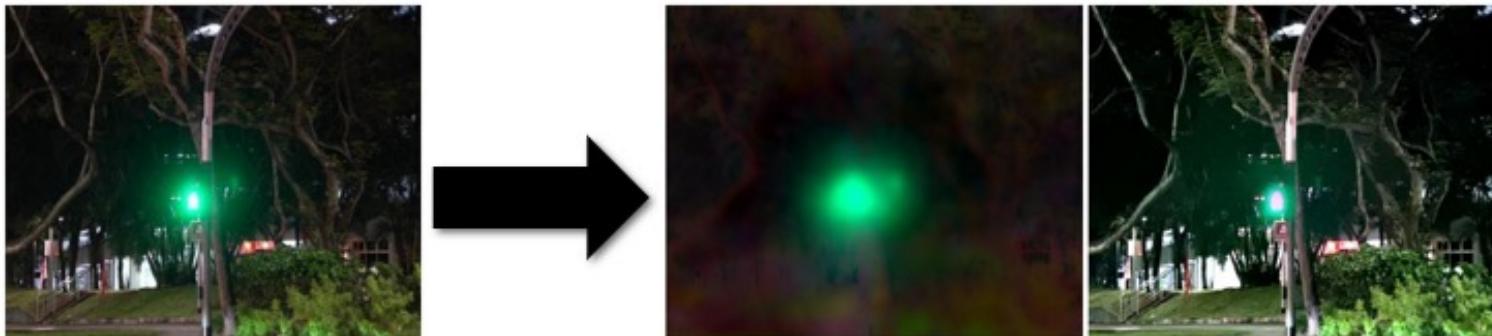
Key Ideas:

- **Unpaired** training data
- Layer Decomposition

Main task: ✓ Boost low-light, at the same time, ✓ suppress light-effects.

Key Ideas & Contributions

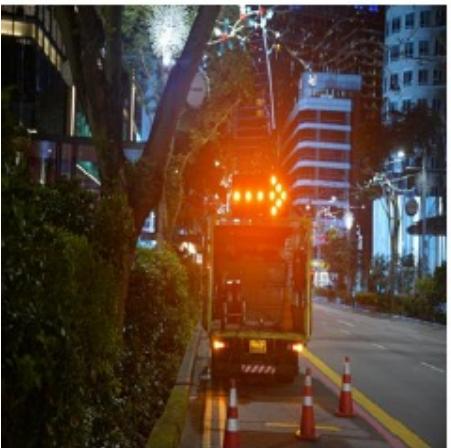
Idea 1: Layer Decomposition



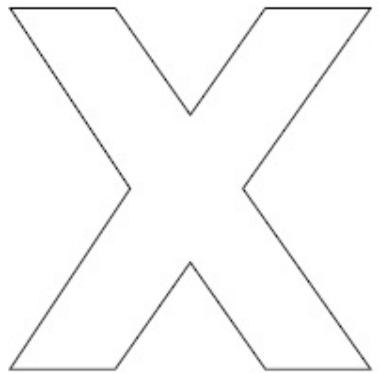
Idea 2: Unpaired Suppression

Paired Input

Domain 1: Light-Effects



Domain 2: Light-Effects-Free

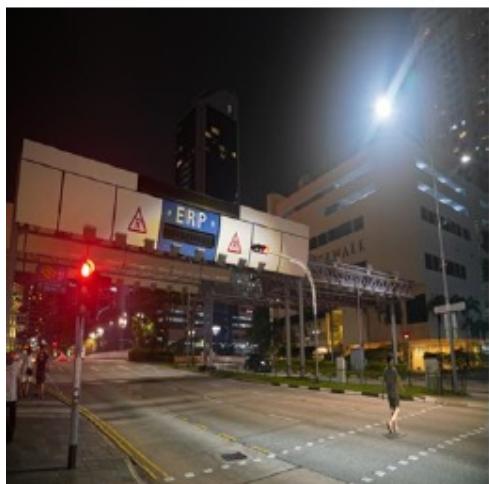


Unpaired Input

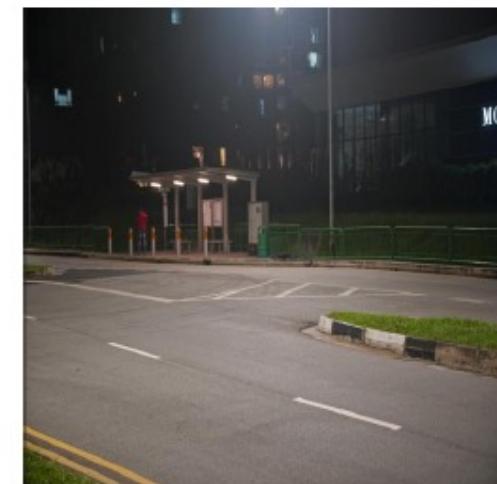
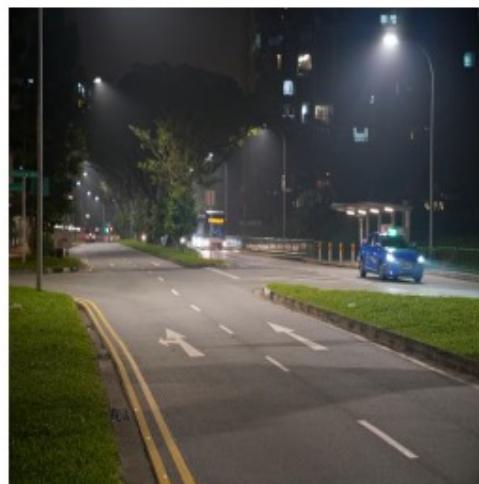
Domain 1: Light-Effects



Domain 2: Light-Effects-Free

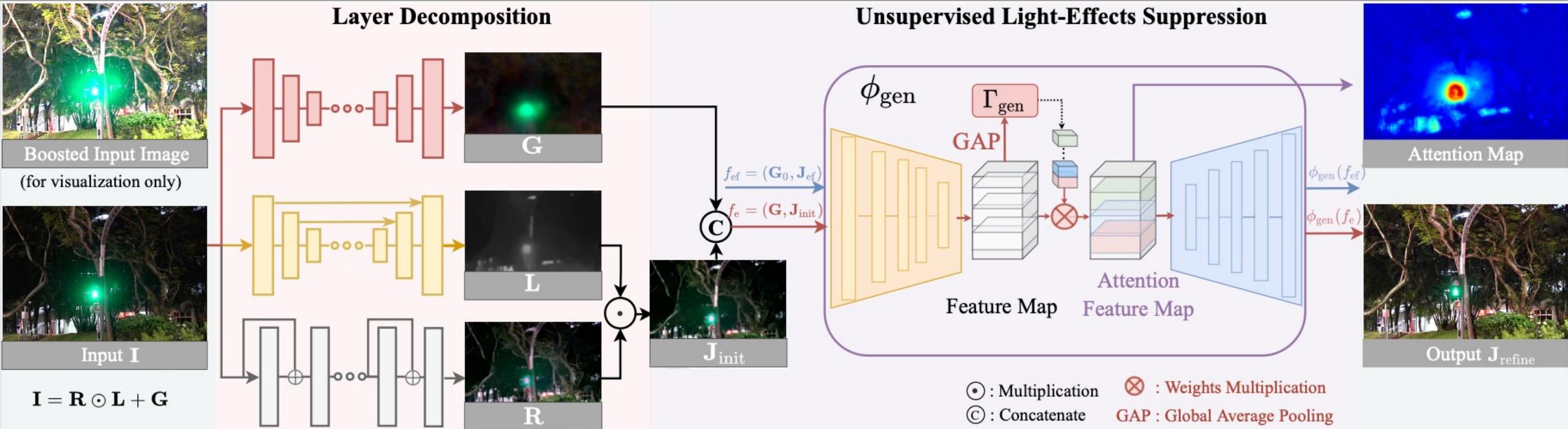


⋮

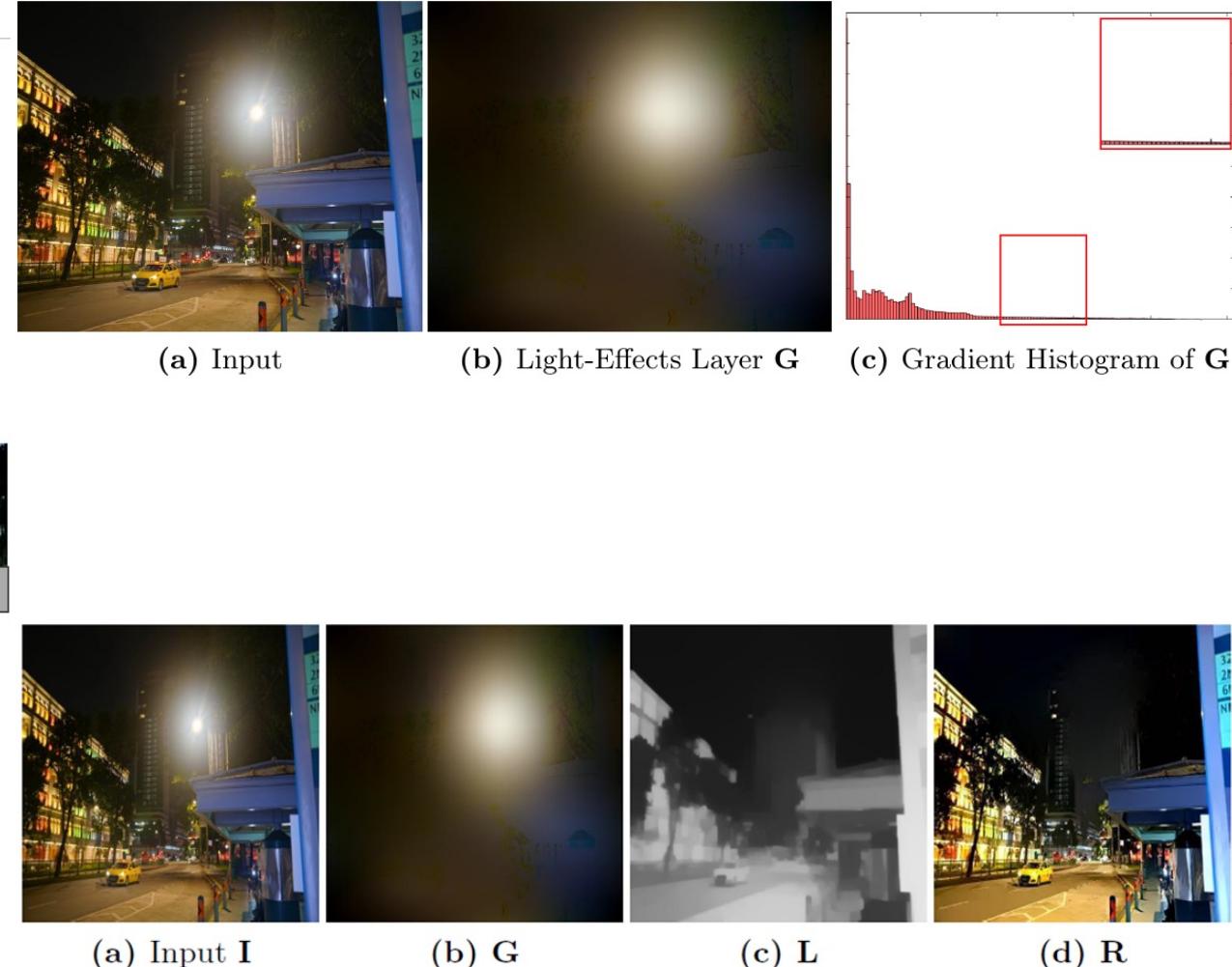
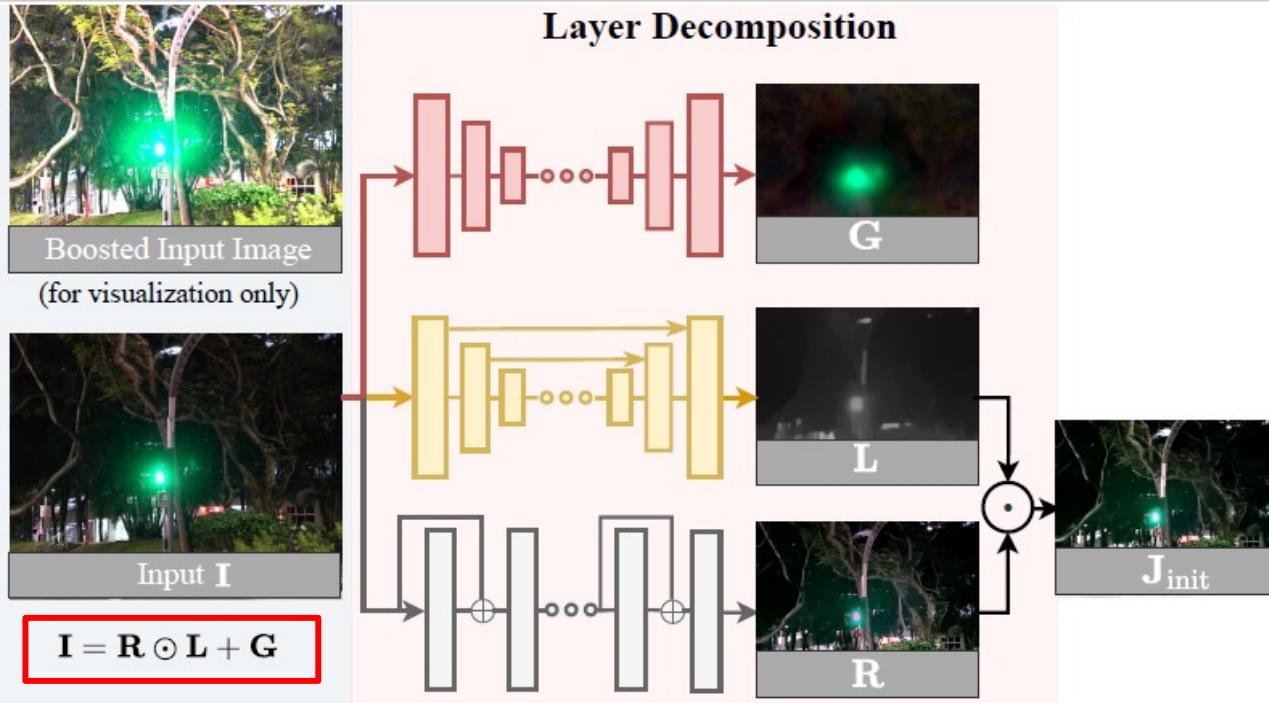


Framework & Losses

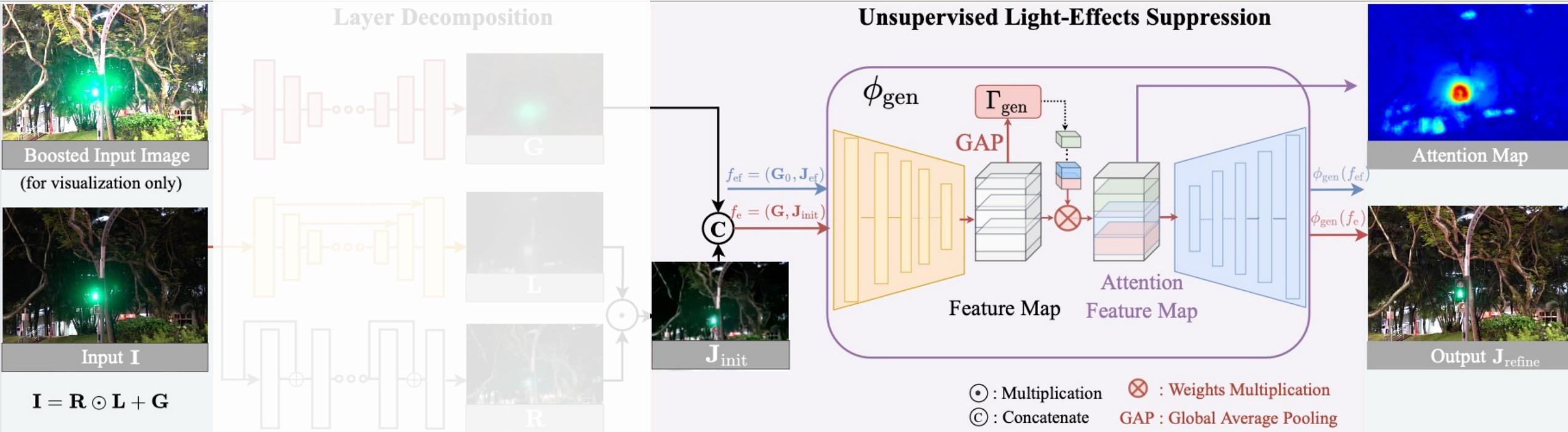
Framework: Overview



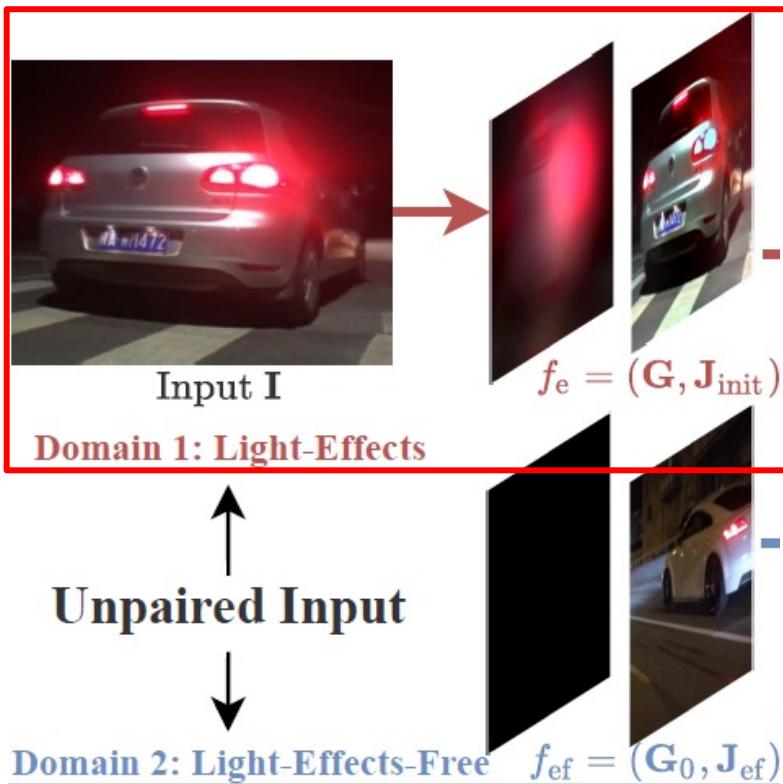
Framework: Layer Decomposition (1/3)



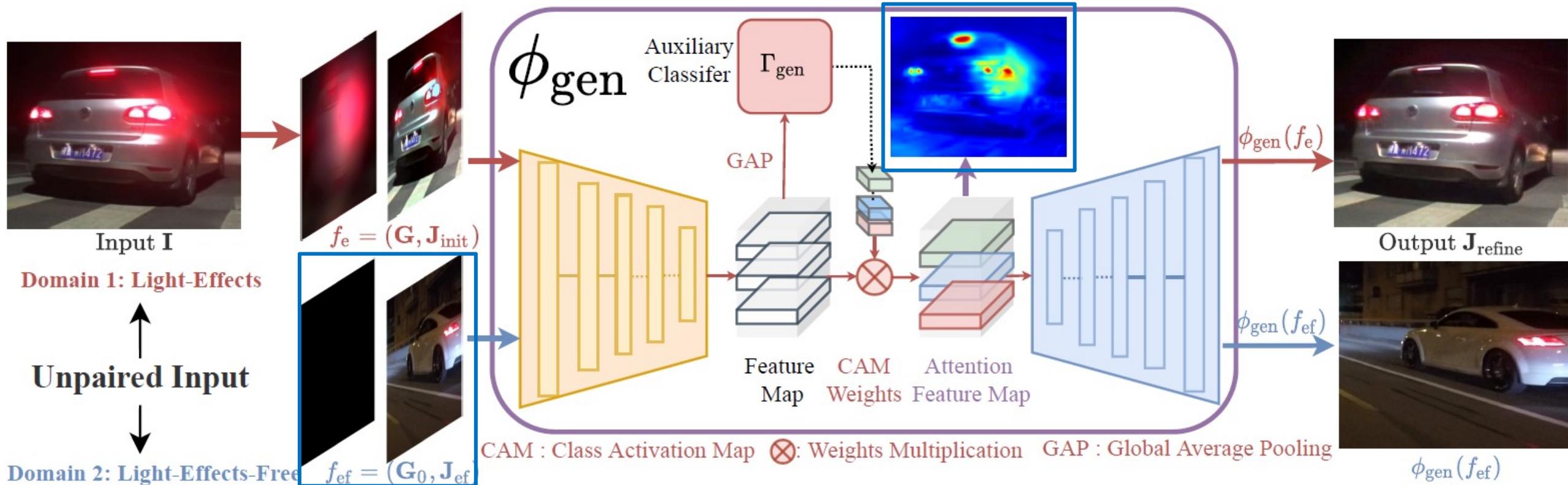
Framework: Overview (2/3)



Framework: Light-effects Suppression



Framework: Light-effects Suppression



Motivation



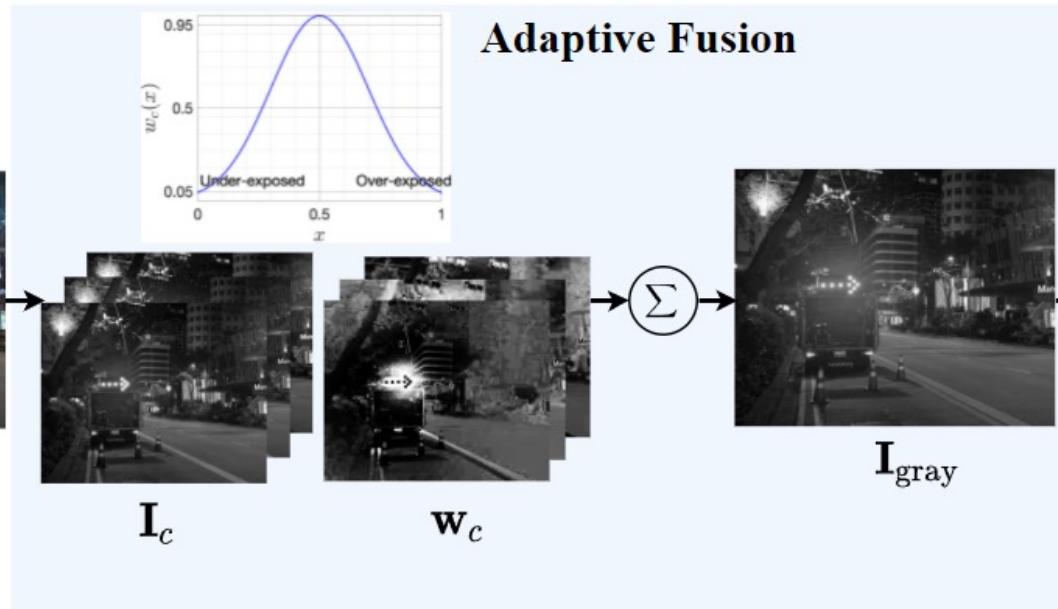
Structure and HF-features Losses (3/3)

\sum : Weighted Sum

$\mathbf{c} \in (\mathbf{r}, \mathbf{g}, \mathbf{b})$



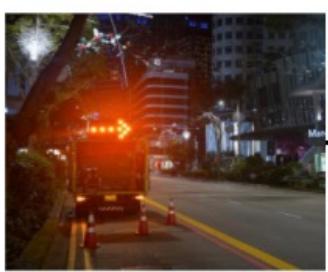
Input \mathbf{I}



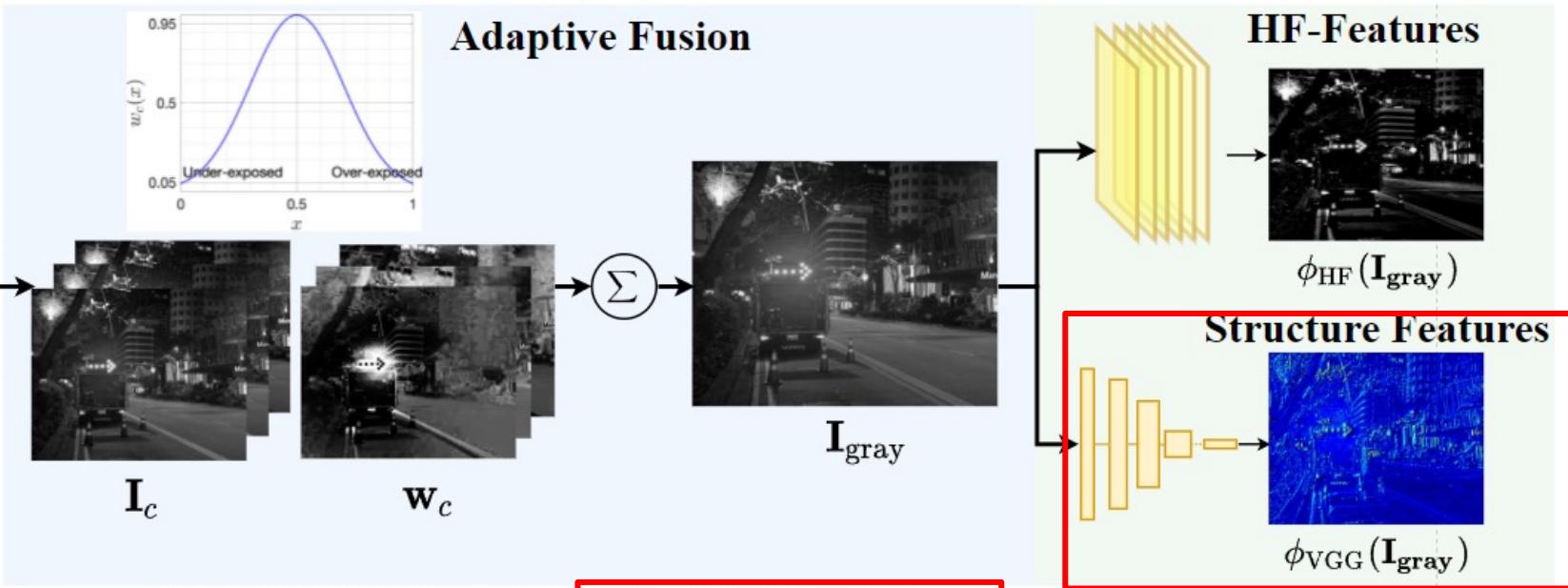
Structure and HF-features Losses

\sum : Weighted Sum

$\mathbf{c} \in (\mathbf{r}, \mathbf{g}, \mathbf{b})$



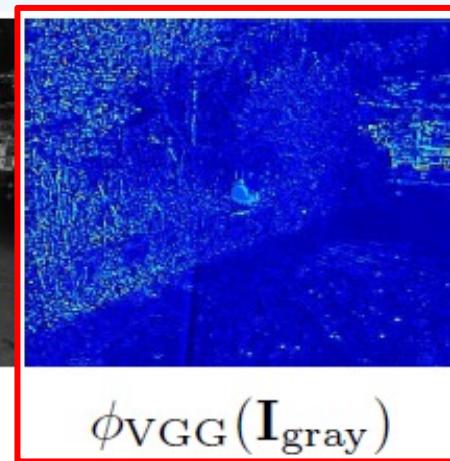
Input \mathbf{I}



Input \mathbf{I}



\mathbf{I}_{gray}



$\phi_{\text{VGG}}(\mathbf{I}_{\text{gray}})$

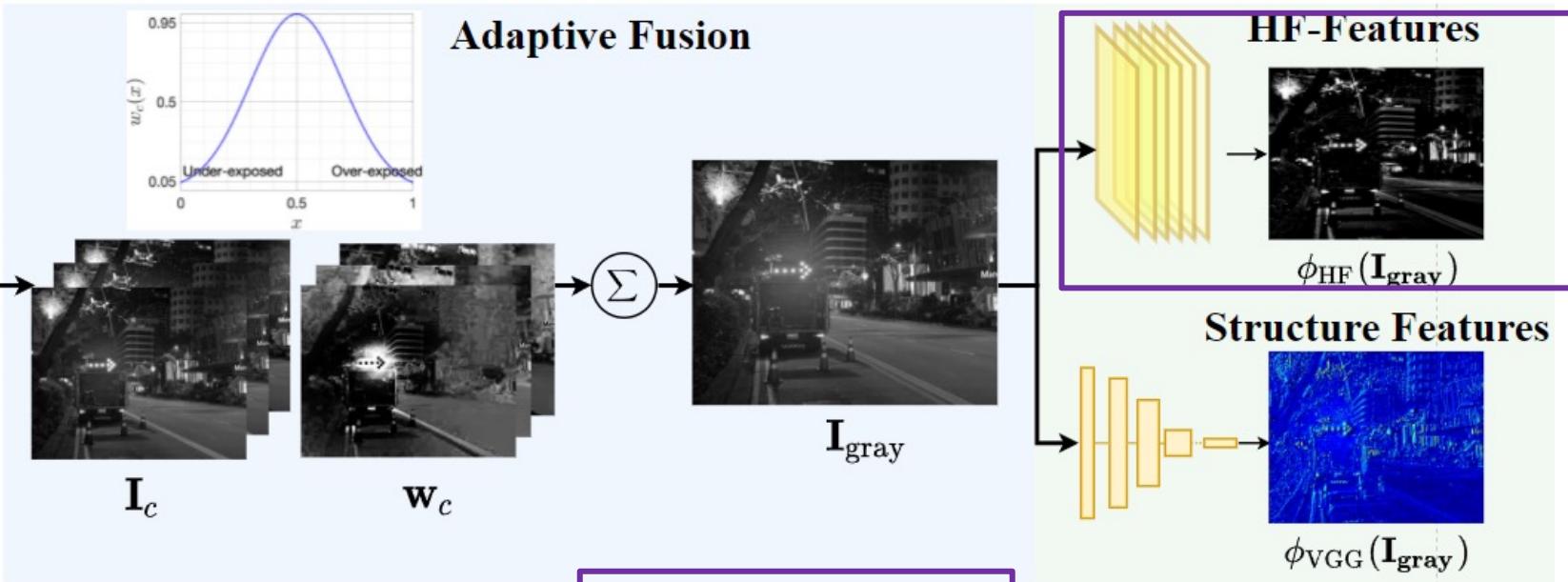
Structure and HF-features Losses

\sum : Weighted Sum

$\mathbf{c} \in (\mathbf{r}, \mathbf{g}, \mathbf{b})$



Input \mathbf{I}

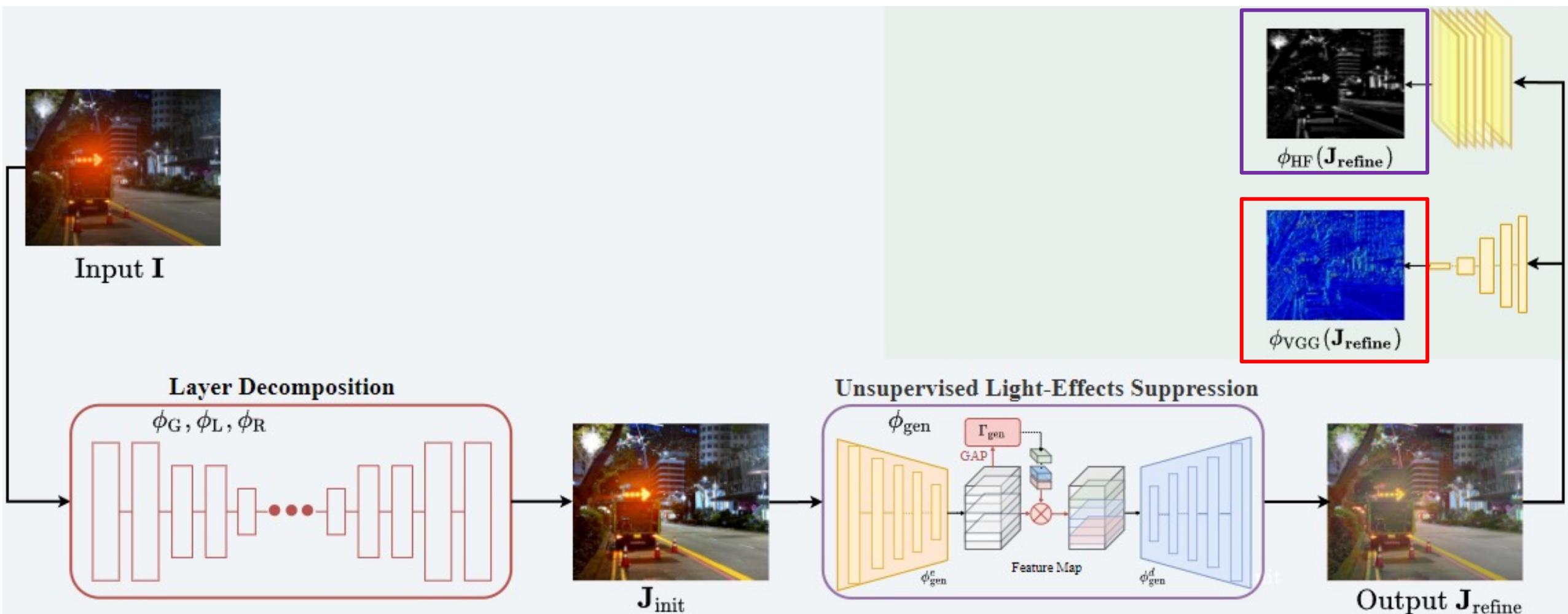


Input \mathbf{I}

\mathbf{I}_{gray}

$\phi_{\text{HF}}(\mathbf{I}_{\text{gray}})$

Structure and HF-features Losses



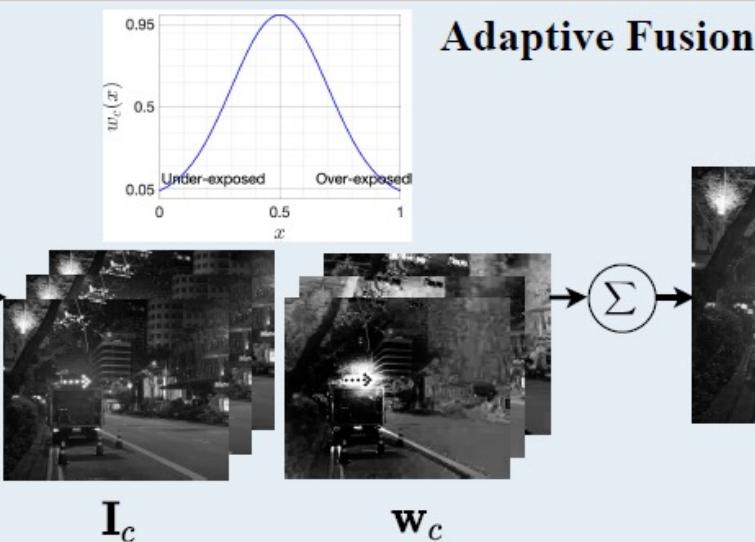
Structure and HF-features Losses

Σ : Weighted Sum

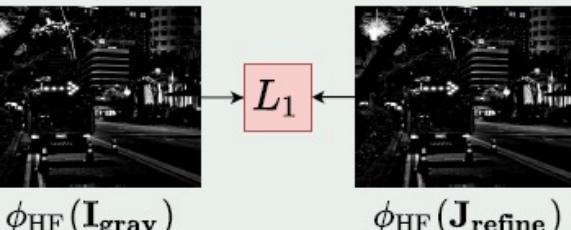
$\mathbf{c} \in (\mathbf{r}, \mathbf{g}, \mathbf{b})$



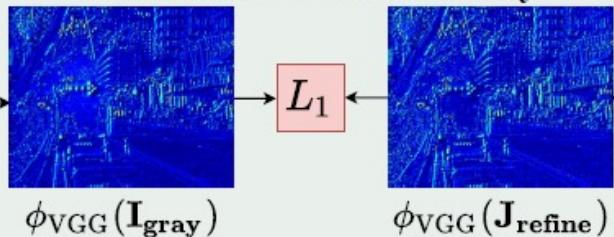
Input \mathbf{I}



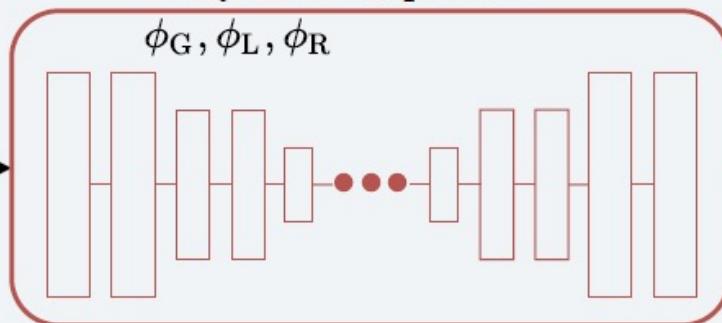
HF-Features Consistency



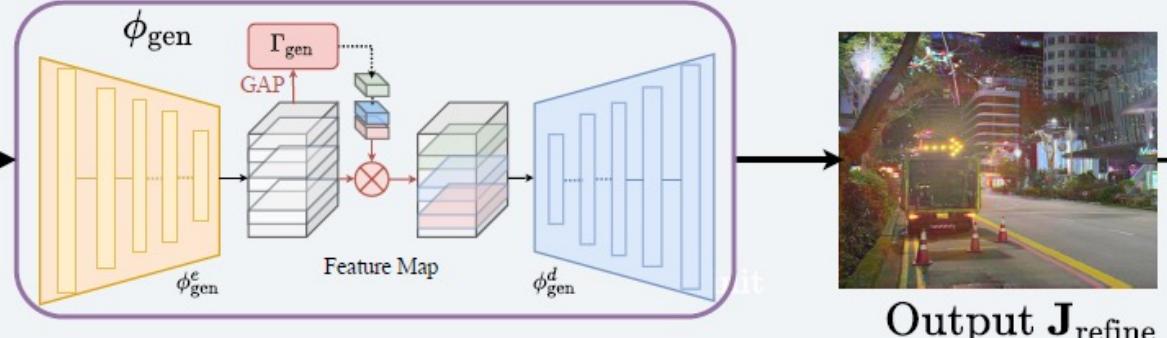
Structure Consistency



Layer Decomposition



Unsupervised Light-Effects Suppression



Results & Conclusion

Results: Light-Effects Suppression



Results: Light-Effects Suppression



Results: Light-Effects Suppression



Results: Light-Effects Suppression



Results: Low-light Enhancement

➤ LOL-test dataset



➤ *LOL-Real* dataset



Input

Ground Truth

Ours

Sharma

EG

Quantitative Results

User study evaluation on the real night data, our method obtained the highest mean (the max score is 7) and lowest standard deviation.

Three Aspects	EG [15]	Afifi [1]	Yan [38]	Zhang [44]	Li [23]	Sharma [32]	Ours
1.Realism↑	3.3 ± 1.5	5.5 ± 1.3	3.7 ± 2.0	3.5 ± 1.6	3.1 ± 1.8	2.8 ± 1.5	6.1 ± 0.8
2.L.E. Supp.↑	1.7 ± 0.8	3.1 ± 1.3	4.6 ± 1.4	3.9 ± 1.1	5.2 ± 1.2	3.0 ± 1.5	6.6 ± 0.7
3.Visibility↑	3.1 ± 1.6	4.2 ± 1.5	4.7 ± 1.5	3.7 ± 1.1	3.8 ± 1.5	3.0 ± 1.4	6.4 ± 0.7

→ **realistic**

→ **light-effects suppressed**

→ **good visibility**

Quantitative light-effects suppression comparison on the night data.

Learning	-	UL	ZSL	SL	SL	SSL	Opti	Opti	SSL	UL
Datasets	Metrics	EG [15]	ZD+ [19]	RN [7]	Afifi [1]	Yan [38]	Zhang [44]	Li [23]	Sharma [32]	Ours
GTA5 [38]	PSNR↑	10.94	21.13	7.79	15.47	26.99	20.92	21.02	8.14	29.79
	SSIM↑	0.31	0.68	0.23	0.53	0.85	0.65	0.64	0.29	0.88
Syn-light-effects [27]	PSNR↑	7.38	7.84	6.39	11.31	14.88	16.30	14.66	14.00	16.95
	SSIM↑	0.17	0.20	0.16	0.35	0.23	0.38	0.37	0.37	0.39

Quantitative comparisons on the *LOL-Real* dataset.

Learning	NA	Opti	Opti	Opti	ZSL	ZSL	ZSL	ZSL	SL
Method	Input	JED [29]	RRM [21]	SRIE [9]	RDIP [48]	MIRNet [43]	RRDNet [50]	ZD [13]	RUAS [24]
PSNR↑	9.72	17.33	17.34	17.34	11.43	12.67	14.85	20.54	15.33
SSIM↑	0.18	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 [25]	RN [7]	DUPE [34]	SICE [6]	Afifi [1]	DRBN [41]	EG [15]	Sharma [32]	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

Quantitative comparisons on the LOL-test dataset

Learning	Method	LOL-test			
		MSE($\times 10^3$)↓	PSNR↑	SSIM↑	LPIPS↓
Opti	LIME [14]	-	16.760	0.560	0.350
SL	RetinexNet [7]	1.651	16.774	0.462	0.474
	KinD++ [47]	1.298	17.752	0.760	0.198
	Afifi [1]	4.520	15.300	0.560	0.392
	RUAS [24]	3.920	18.230	0.720	0.350
ZSL	ZeroDCE [13]	3.282	14.861	0.589	0.335
SSL	DRBN [40]	2.359	15.125	0.472	0.316
UL	EnlightenGAN [15]	1.998	17.483	0.677	0.322
SSL	Sharma [32]	3.350	16.880	0.670	0.315
UL	Ours	1.070	21.521	0.763	0.235

Conclusion

- We presented an **unsupervised learning** framework for night image enhancement, which boost dark regions and suppress light-effects simultaneously.
- With unsupervised structure and HF-features consistency loss, our method **restore the background details**.



Input

w/o $\mathcal{L}_{\text{gray-feat}}$

w/ $\mathcal{L}_{\text{gray-feat}}$

Thank you!

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CODES AND MODEL:

[HTTPS://GITHUB.COM/JINYEYING/NIGHT-ENHANCEMENT](https://github.com/JinYeYing/Night-Enhancement)

