NUS National University of Singapore

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

Yeying Jin[1], Wenhan Yang[2], Robby T. Tan[1,3]

[1]National University of Singapore; [2]Nangyang Technological University; [3]Yale-NUS College

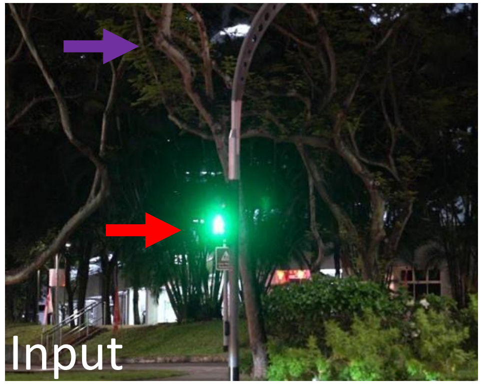
Night Image Problem

- Low Light:

- Light-Effects/Glare/Floodlight:

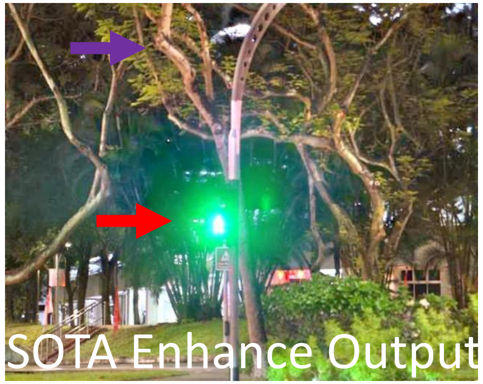
Motivation

- Existing low-light enhancement methods:



✓ Enhance low-light regions

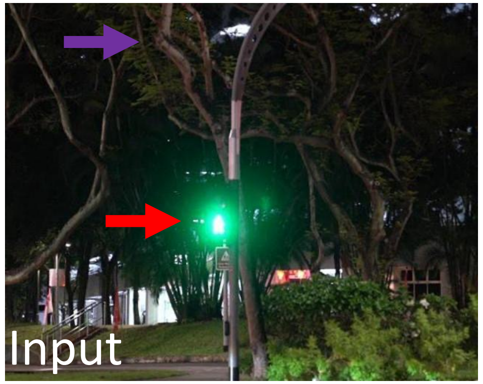
× Over-enhance light-effects regions



Low-light regions

Light-effects regions

- Existing night dehazing methods:



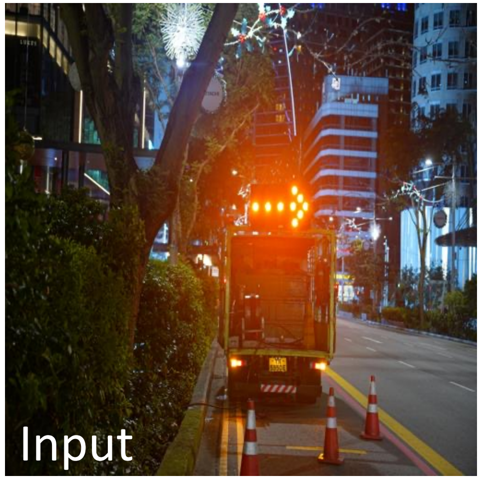
× Enhance low-light regions

✓ Suppress glow; × Suppress light-effects

Main task: Boost dark regions, at the same time, suppress light-effects.

Challenge

- Lack of **paired** training data, hard to collect ground truth



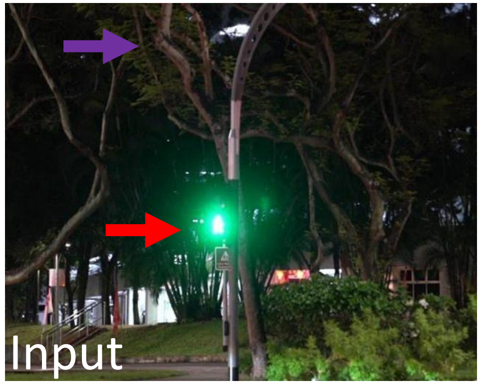
- Rendering physically correct night light-effects images is challenging

We propose an **unsupervised** night image enhancement method.

- Model-based Layer Decomposition
- Unpaired Light-Effects Suppression

Contributions

- To boost dark regions, at the same time, suppress light-effects.

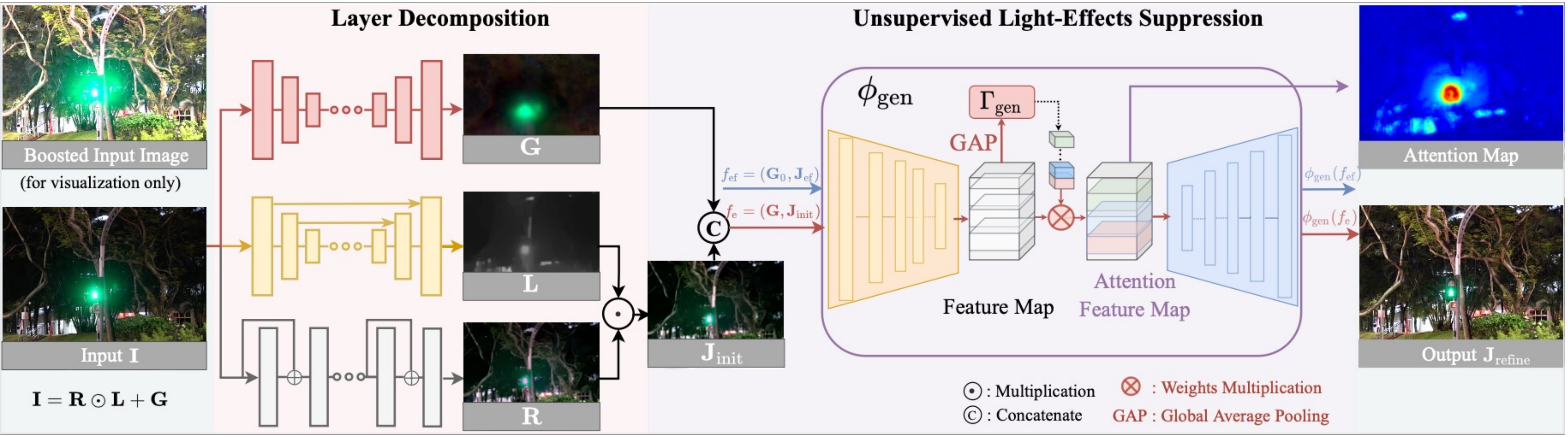


✓ Enhance low-light regions

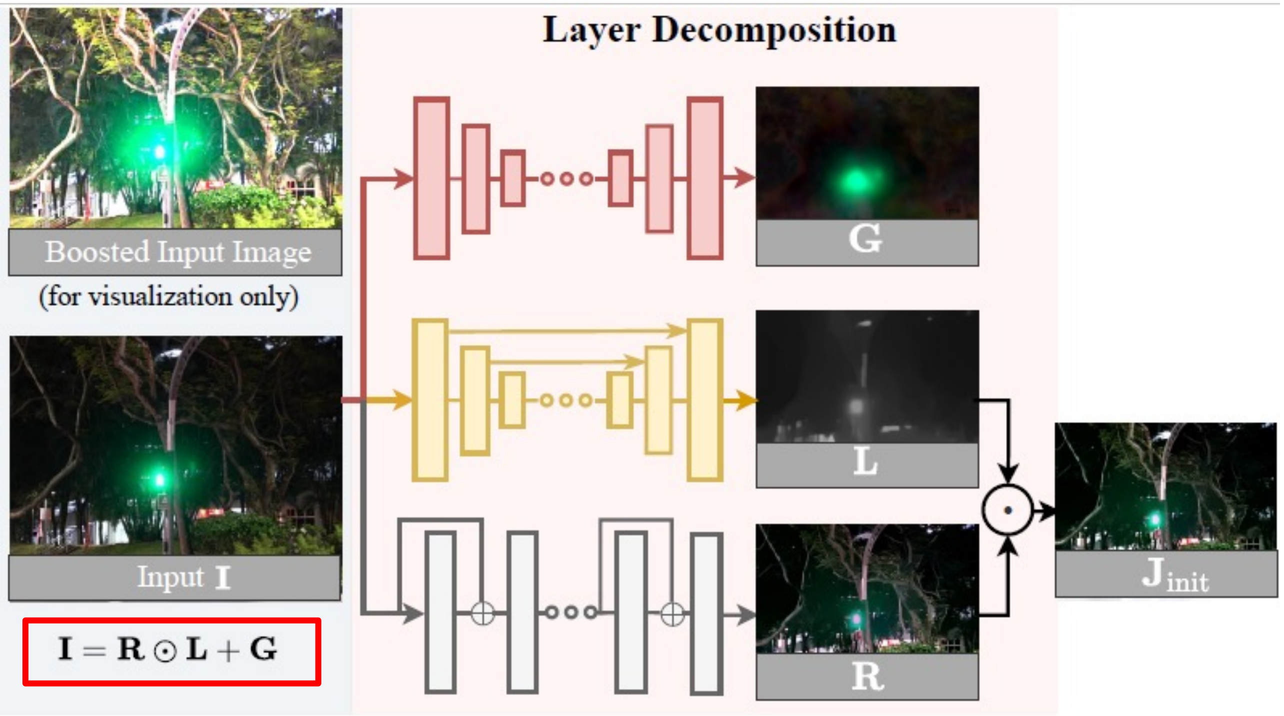
✓ Suppress light-effects regions

- We introduce an **unsupervised learning network**, that integrates layer decomposition and light-effects suppression.
- We propose utilizing the light-effects layer as guidance, to distinguish light-effects from background regions, e.g., **white/multi-colored light-effects**.
- We introduce **unsupervised losses** based on the structure and HF-features consistency, to **restore the background details.**

Framework: Overview



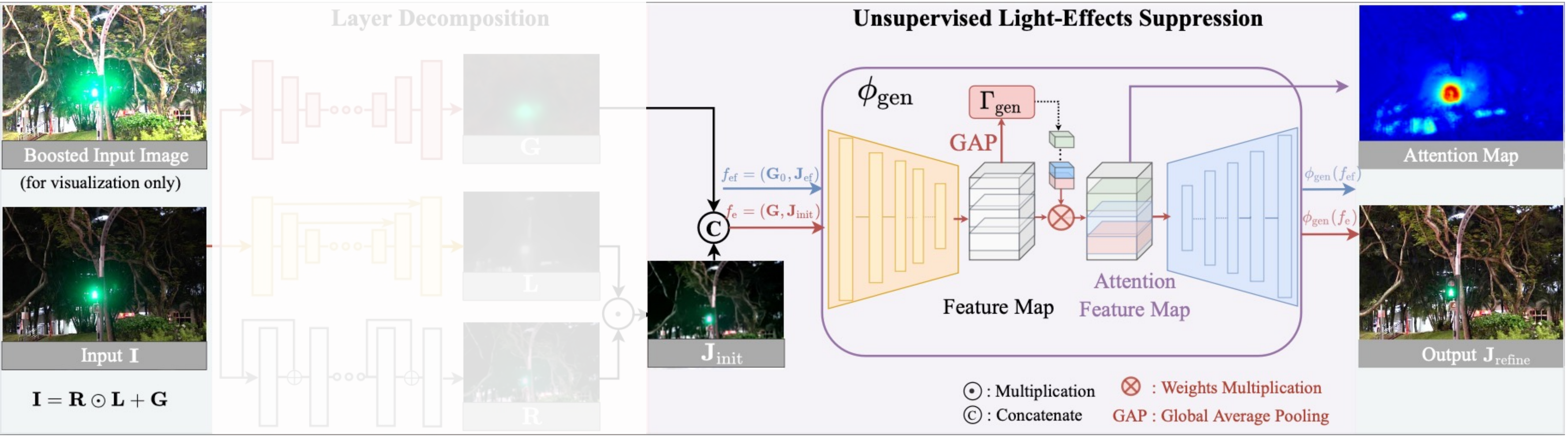
Framework: Layer Decomposition



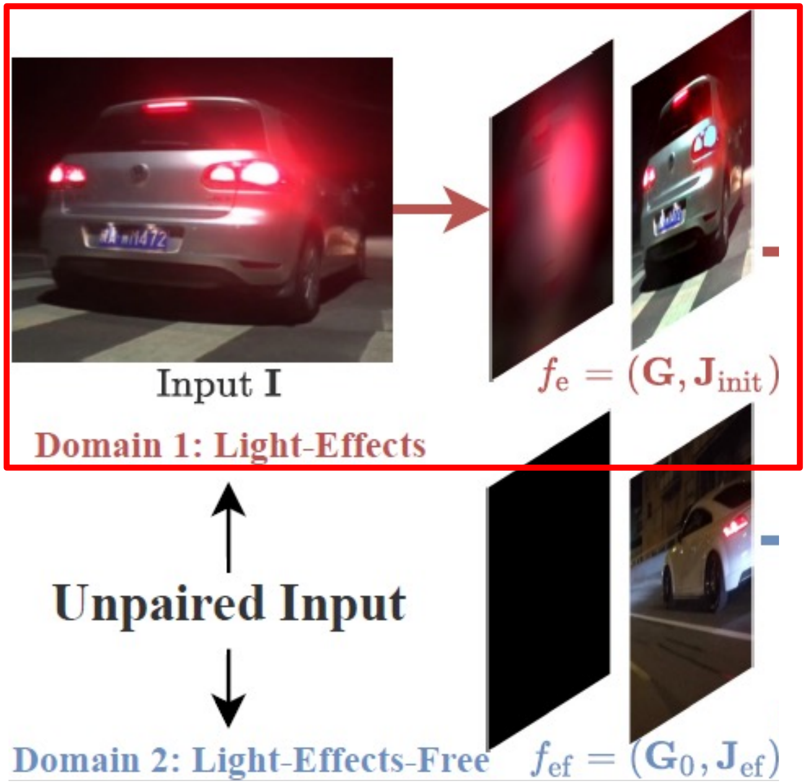
(a) Input (b) Light-Effects Layer **G** (c) Gradient Histogram of **G**

(a) Input **I** (b) **G** (c) **L** (d) **R**

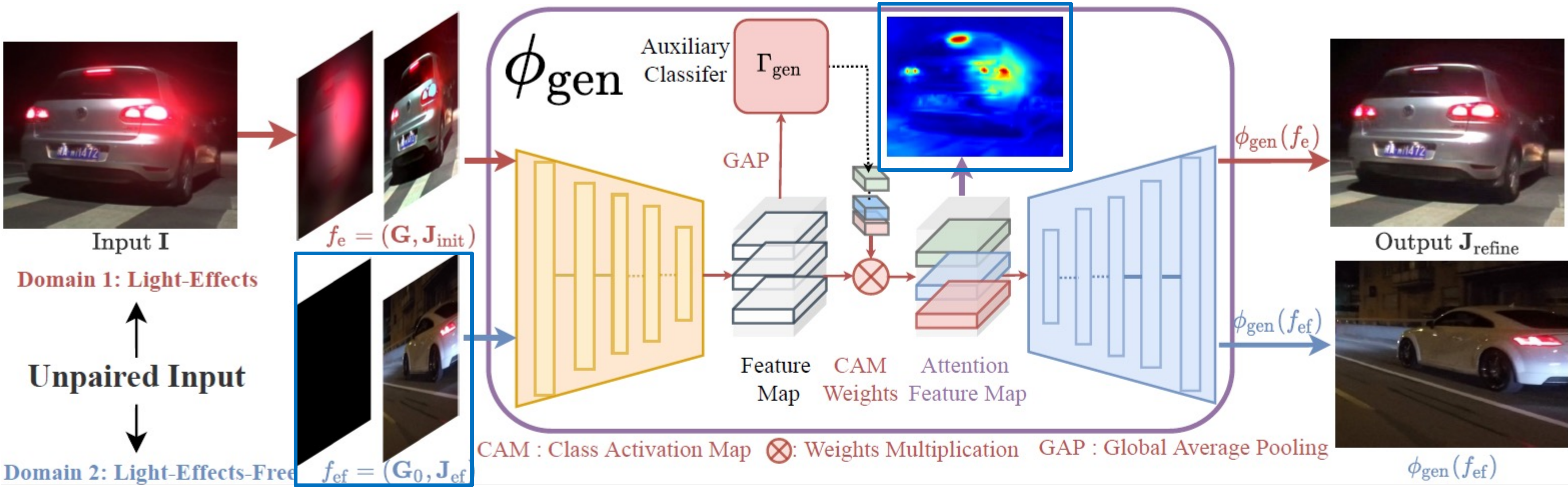
Framework: Overview



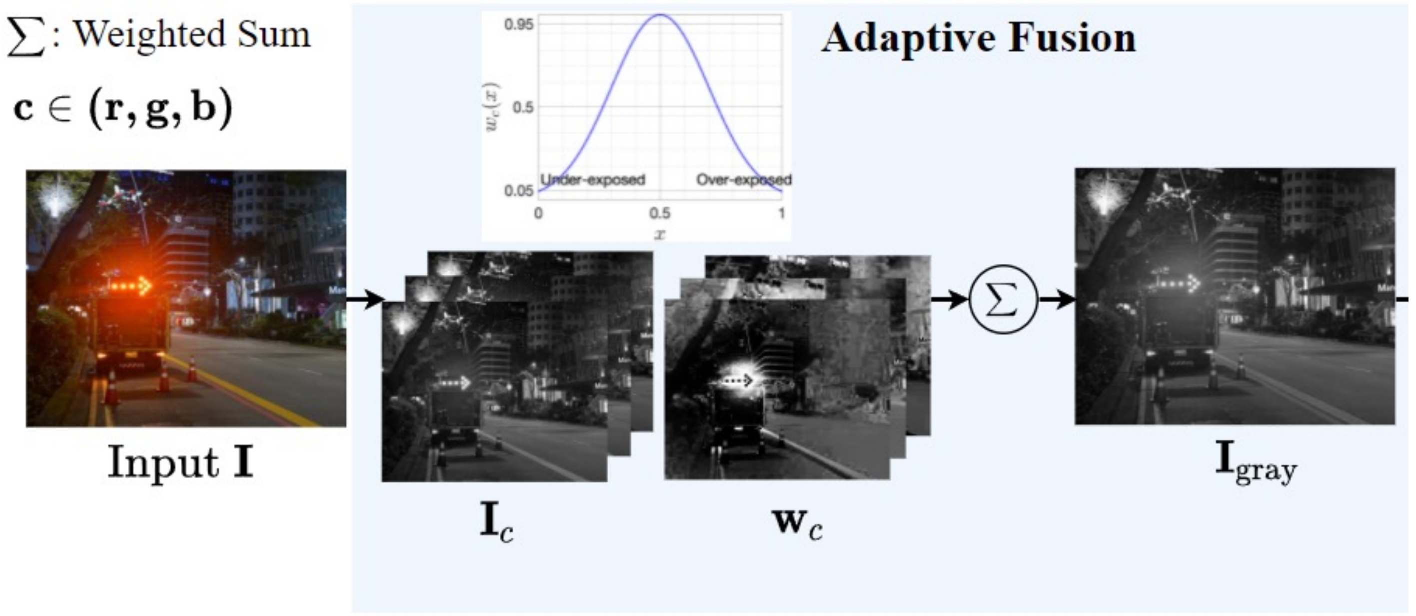
Framework: Light-effects Suppression



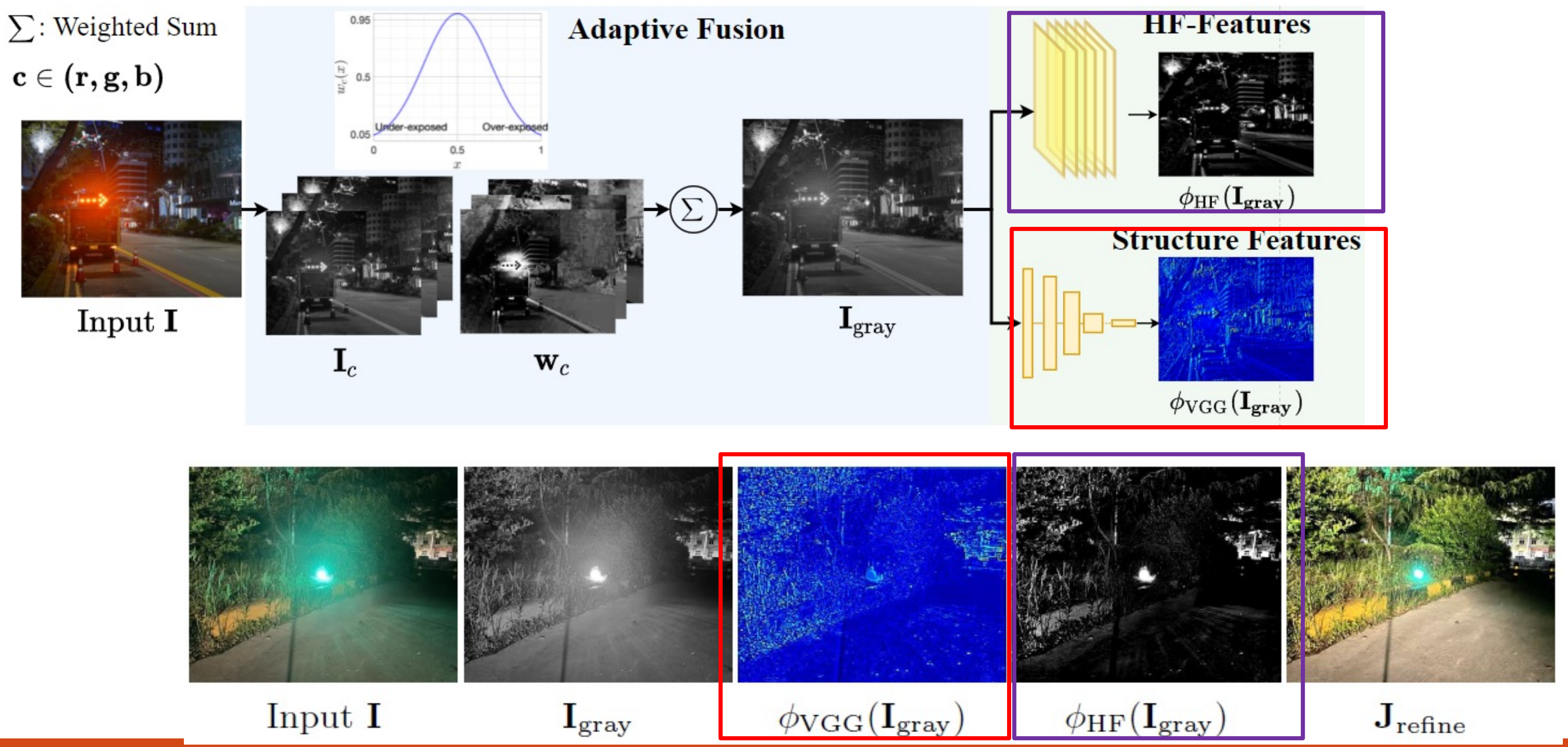
Framework: Light-effects Suppression



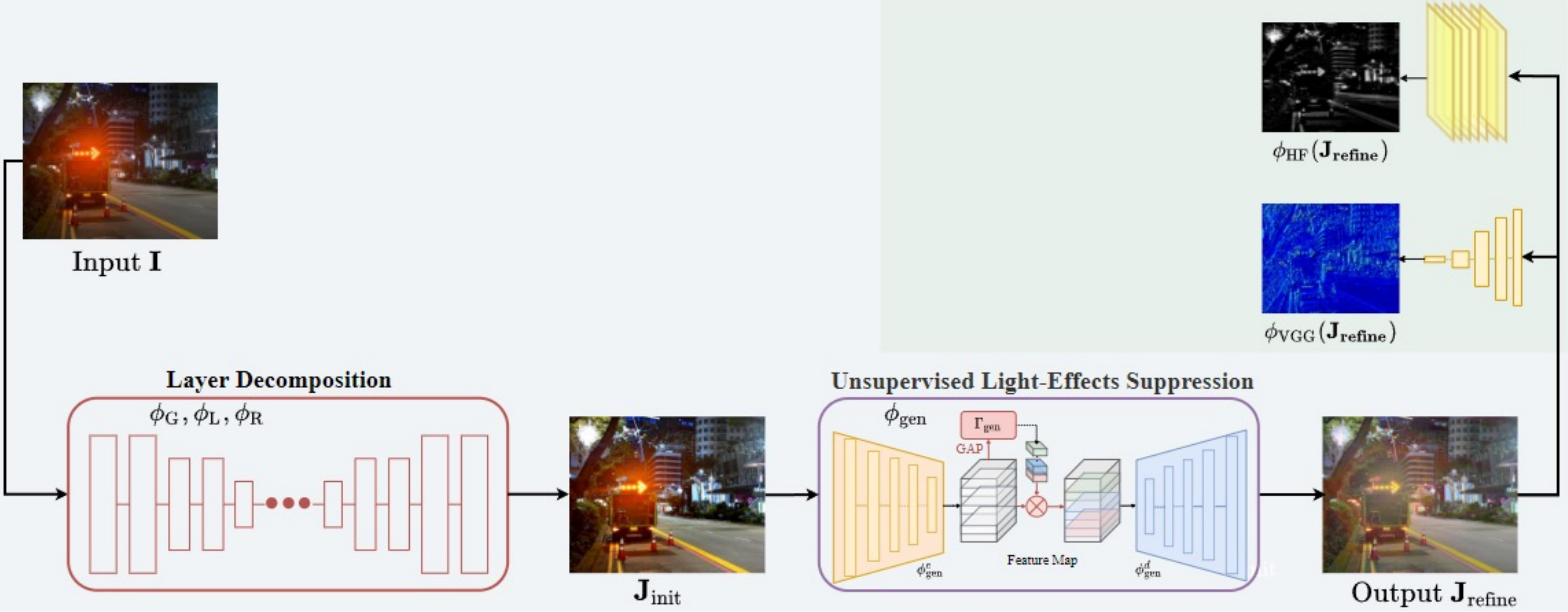
Structure and HF-features Losses



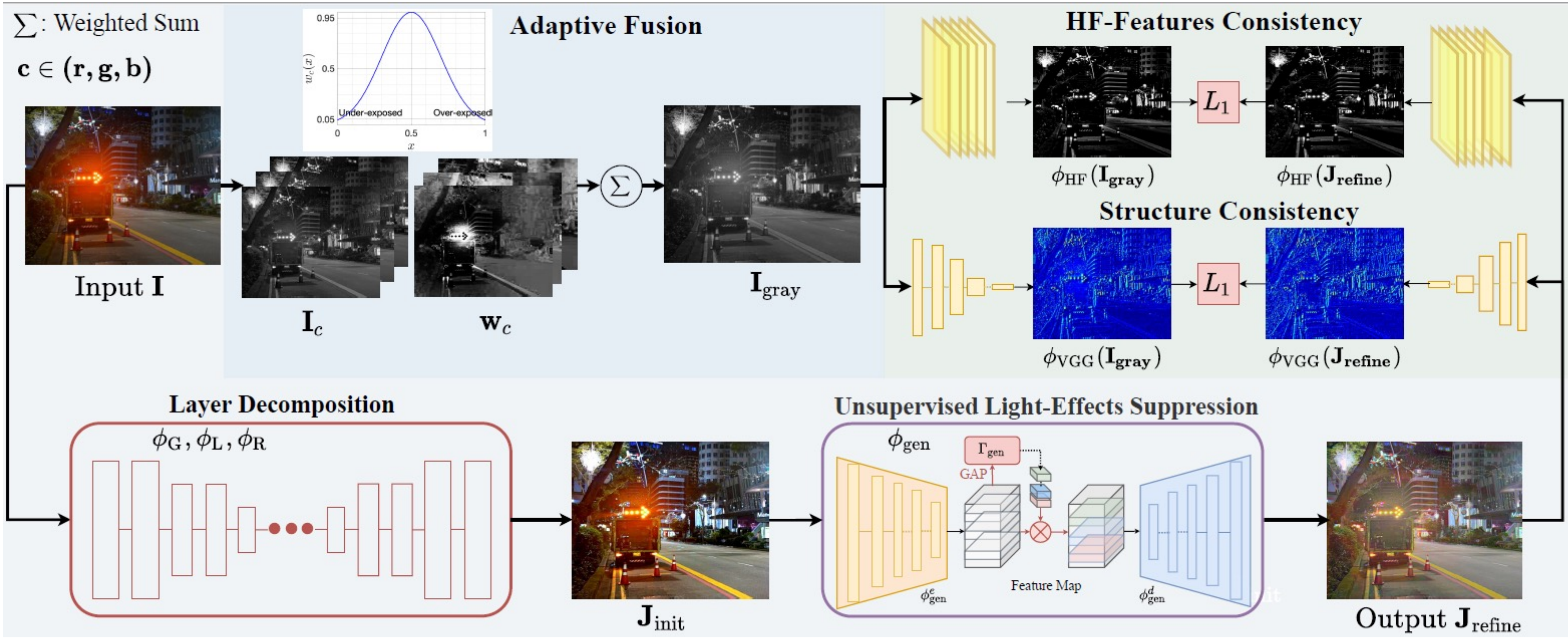
Structure and HF-features Losses



Structure and HF-features Losses



Structure and HF-features Losses



Results on Light-Effects Suppression

➢User Study

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	$\mathbf{6.1 \pm 0.8}$
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	$\mathbf{6.6 \pm 0.7}$
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	$\mathbf{6.4 \pm 0.7}$

realistic

light-effects suppressed

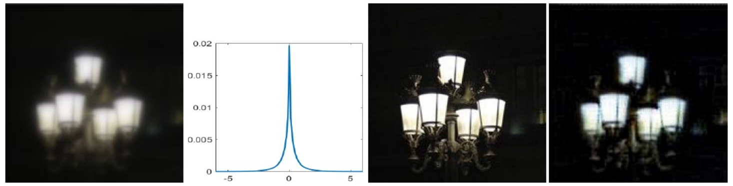
good visibility

➢Quantitative Evaluation

Quantitative light-effects suppression comparison on the night data.

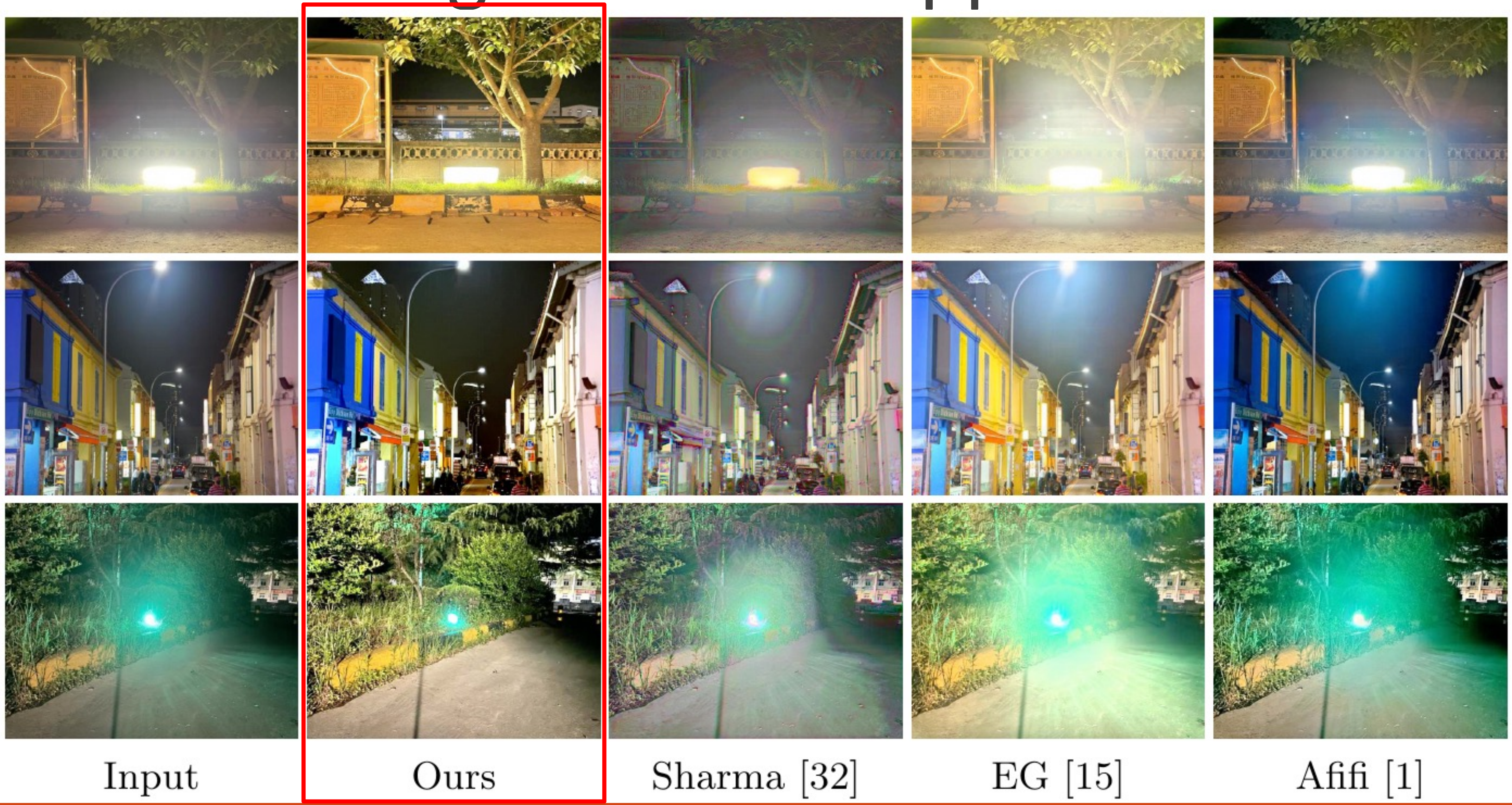
Learning	-	UL	ZSL	SL	SL	SSL	Opti	Opti	SSL	UL
Datasets	Metrics	EG [15]	ZD+ [19]	RN [7]	Afifi [1]	Yan [38]	Zhang [44]	Li [23]	Sharma [32]	Ours
GTA5 [38]	PSNR↑	10.94	21.13	7.79	15.47	26.99	20.92	21.02	8.14	**29.79**
	SSIM↑	0.31	0.68	0.23	0.53	0.85	0.65	0.64	0.29	**0.88**
Syn-light-effects [27]	PSNR↑	7.38	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**

Input Ground Truth **Ours**



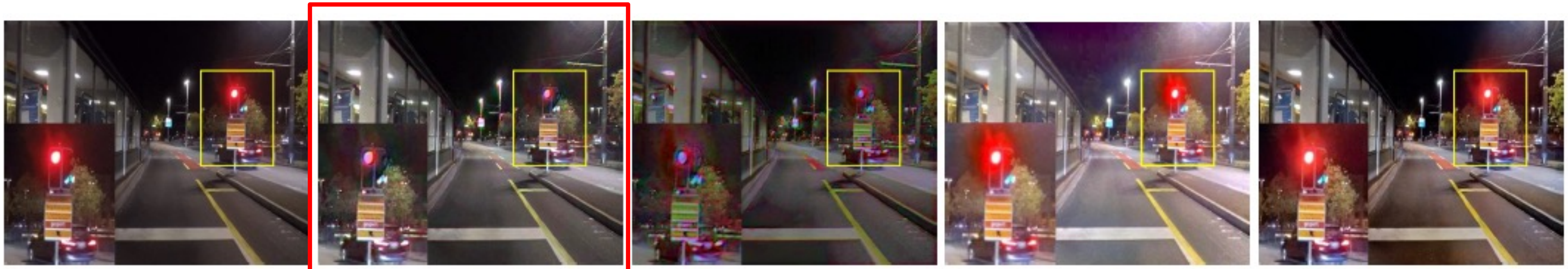
Input APSF Model Ground Truth **Ours**

Results on Light-Effects Suppression



Results on Light-Effects Suppression

- Dark Zurich Dataset



Input | Ours | Sharma [32] | EG [15] | Afifi [1]

Results on Low-light Enhancement

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

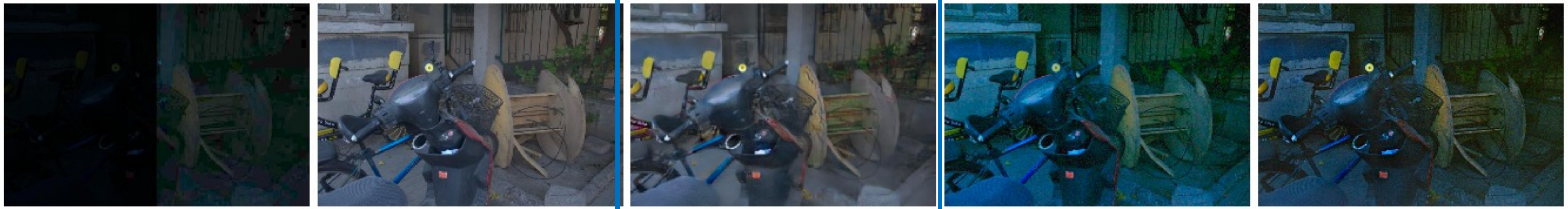
Quantitative comparisons on the *LOL-Real* dataset.

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**

Results on Low-light Enhancement

- LOL-test dataset

- *LOL-Real* dataset

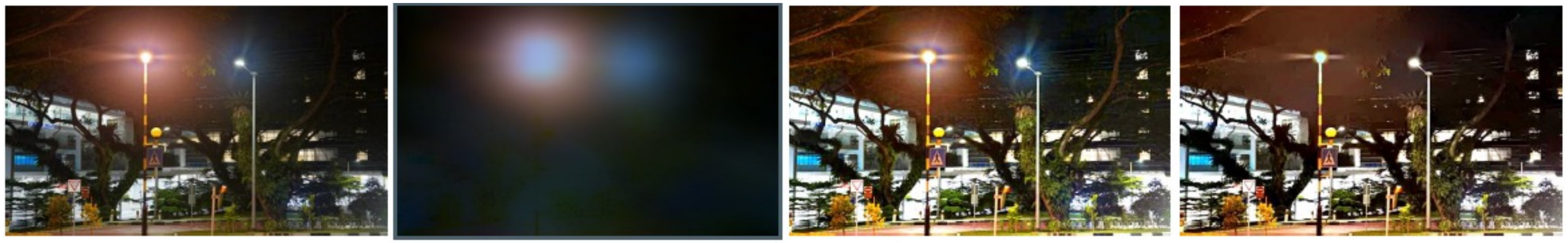


Input Ground Truth Ours Sharma EG

Conclusion

- We presented an **unsupervised learning** framework for night image enhancement, which boost dark regions and suppress light-effects simultaneously.

- With light-effects layer guidance, our method separate **white/multi-colored light-effects** more properly.



Input | Light-Effects Layer | w/o $\mathbf{G}$ guidance | w/ $\mathbf{G}$ guidance

- 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!

JINYEYING@U.NUS.EDU

CODES, DATA AND MODEL:

HTTPS://GITHUB.COM/JINYEYING/NIGHT-ENHANCEMENT