

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

Yeying Jin<sup>1</sup>, Wenhan Yang<sup>2</sup>, Robby T. Tan<sup>1,3</sup>

<sup>1</sup>National University of Singapore; <sup>2</sup>Nangyang Technological University; <sup>3</sup>Yale-NUS College

# Night Image Problem

---

## ➤ Low Light:

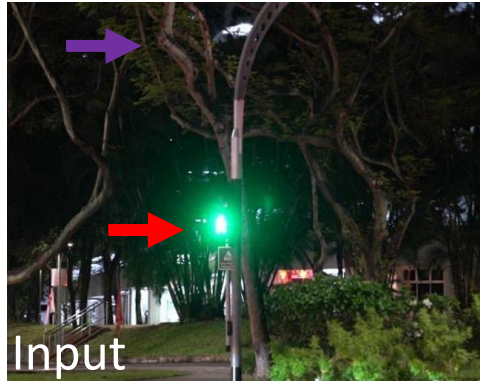


## ➤ Light-Effects/Glare/Floodlight:



# Motivation

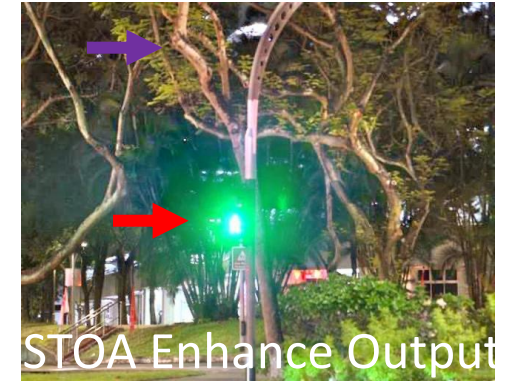
## ➤ Existing low-light enhancement methods:



✓ Enhance low-light regions

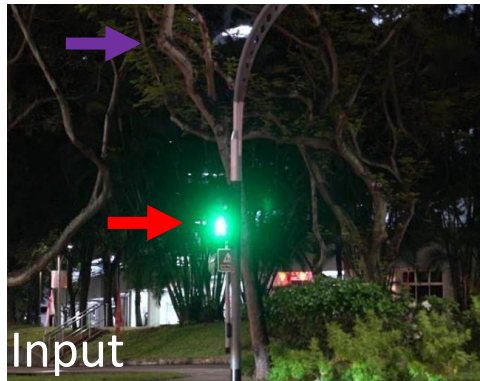


✗ Over-enhance light-effects regions



➡ Low-light regions  
➡ Light-effects regions

## ➤ Existing night dehazing methods:



✗ Enhance low-light regions



✓ Suppress glow; ✗ Suppress light-effects



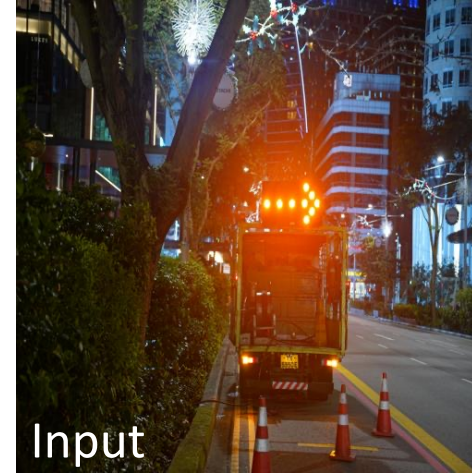
**Main task:** Boost dark regions, at the same time, suppress light-effects.



# Challenge

---

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



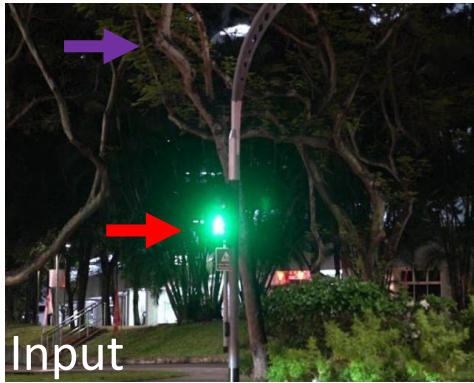
- Rendering physically correct night light-effects images is challenging

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

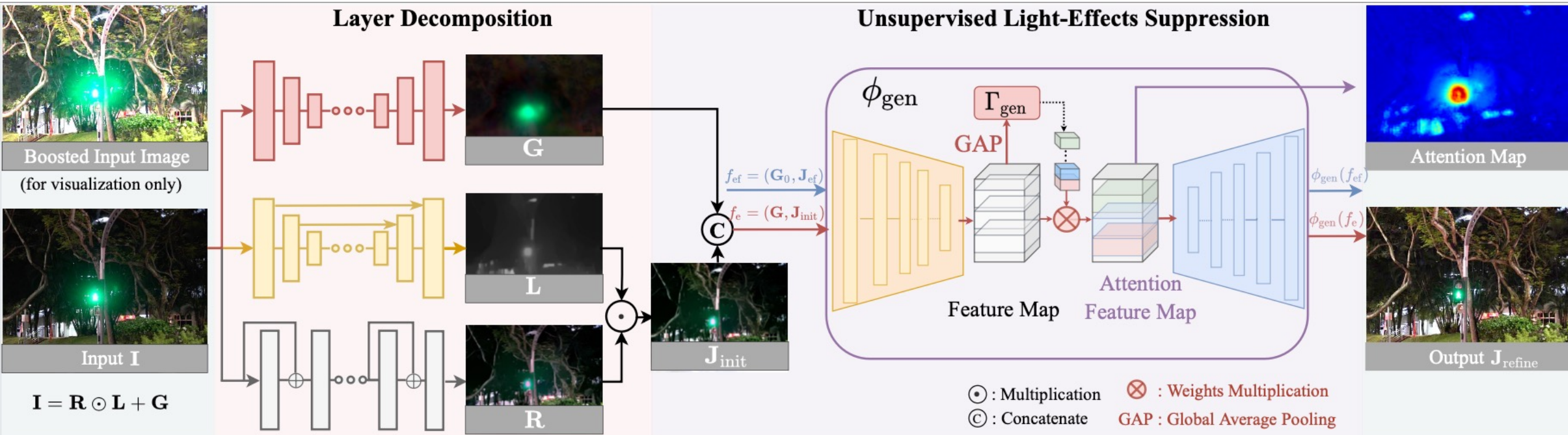


✓ Suppress light-effects regions



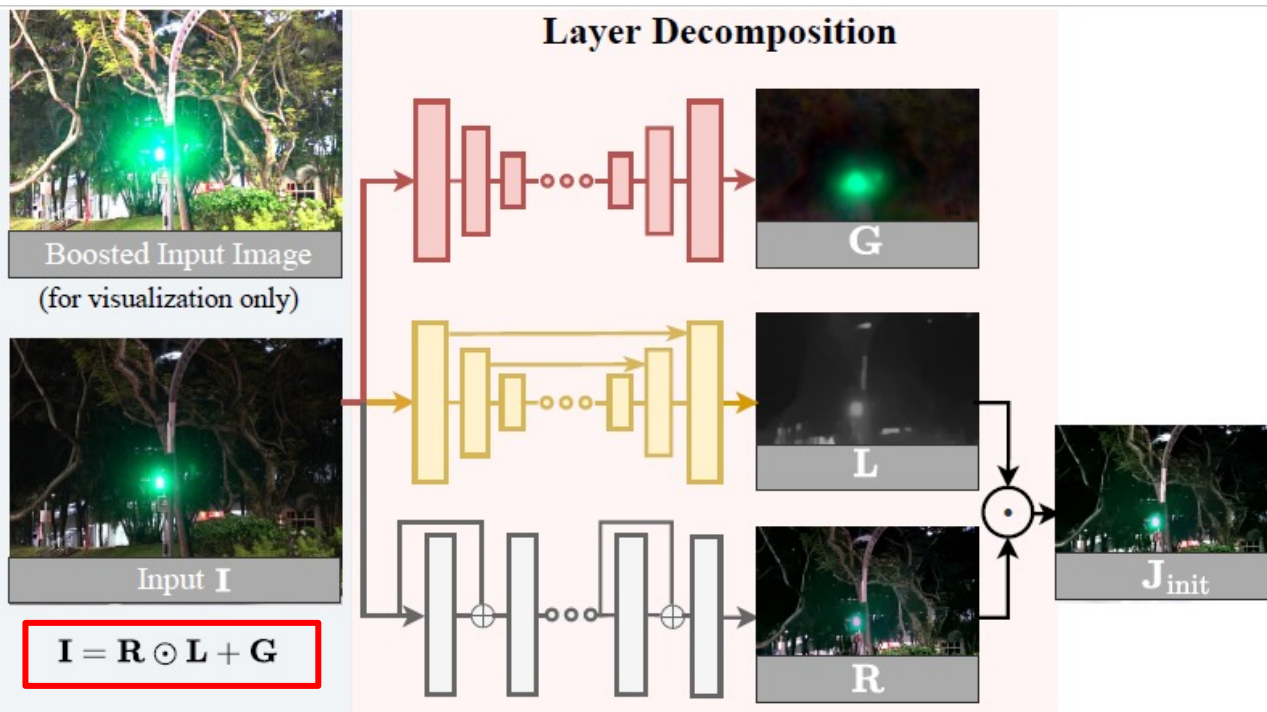
- We introduce an **unsupervised learning network**, that integrates layer decomposition and light-effects suppression.
- We propose utilizing the light-effects layer as guidance, to distinguish light-effects from background regions, e.g., **white/multi-colored light-effects**.
- We introduce **unsupervised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

# Framework: Overview





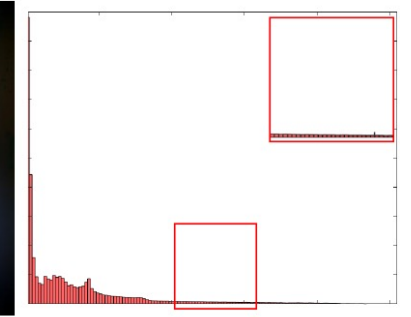
# Framework: Layer Decomposition



(a) Input



(b) Light-Effects Layer  $G$



(c) Gradient Histogram of  $G$



(a) Input  $I$



(b)  $G$

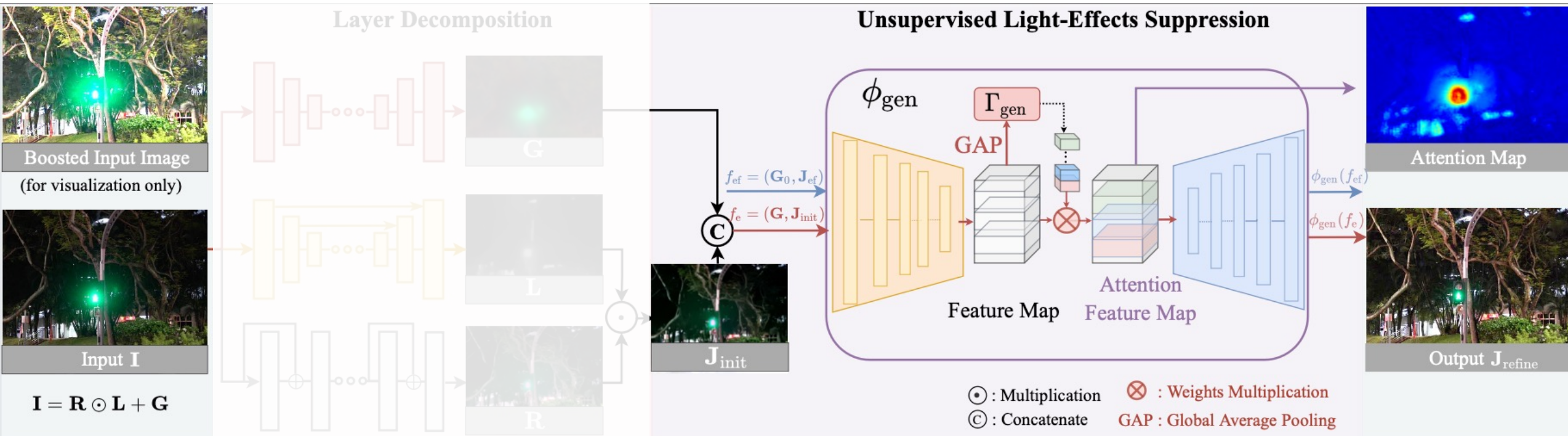


(c)  $L$



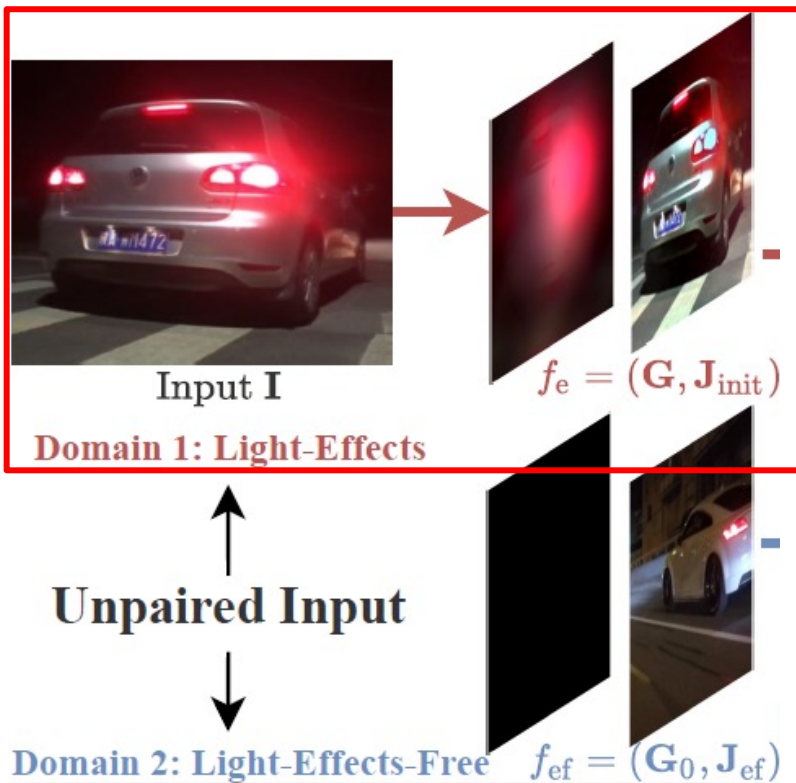
(d)  $R$

# Framework: Overview

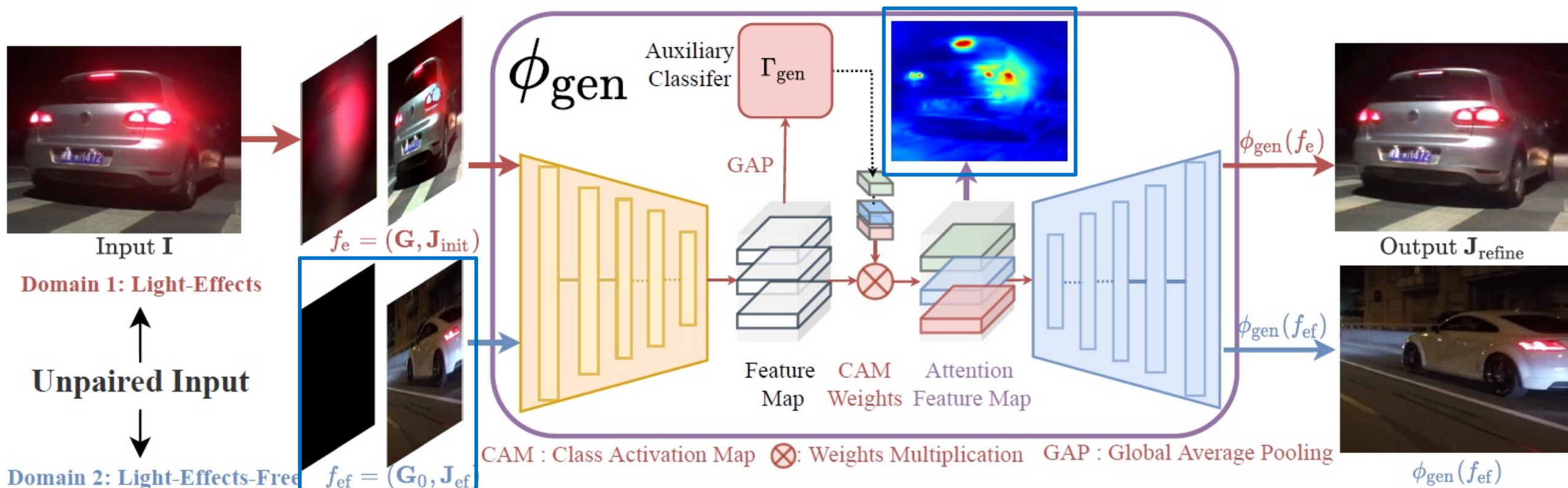




# Framework: Light-effects Suppression



# Framework: Light-effects Suppression



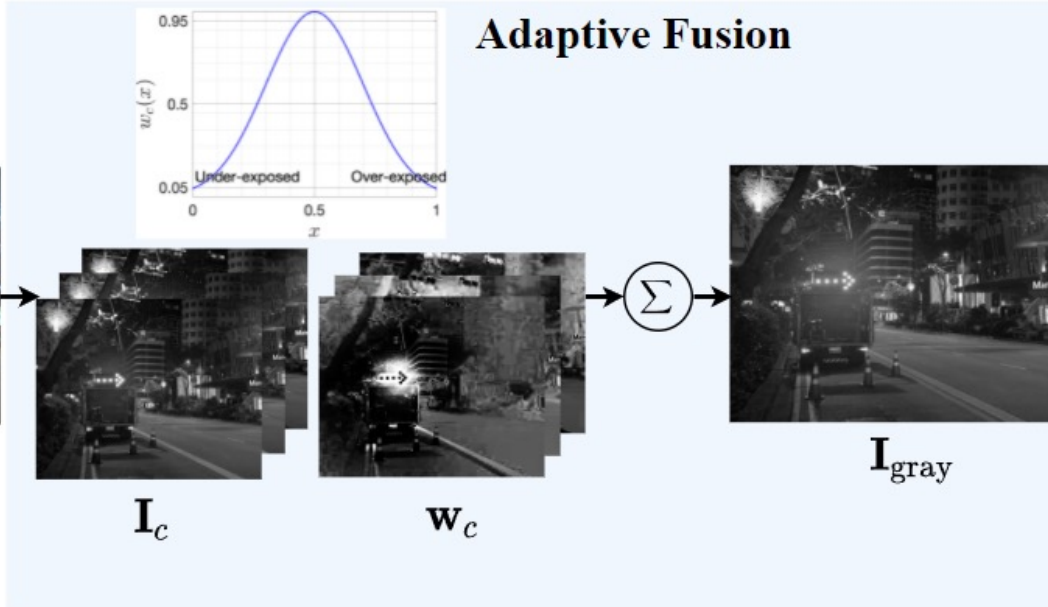
# Structure and HF-features Losses

$\Sigma$ : Weighted Sum

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



Input  $\mathbf{I}$

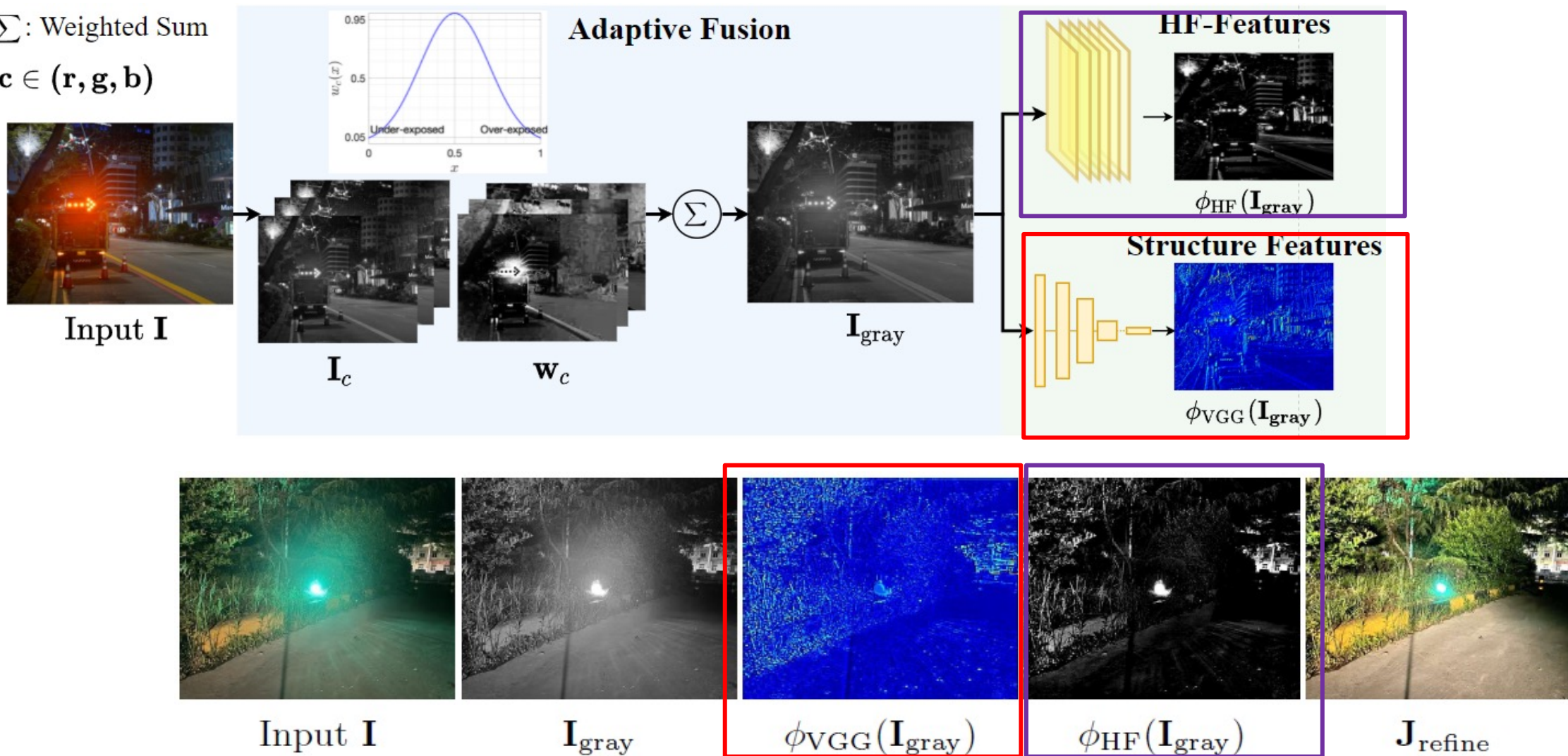




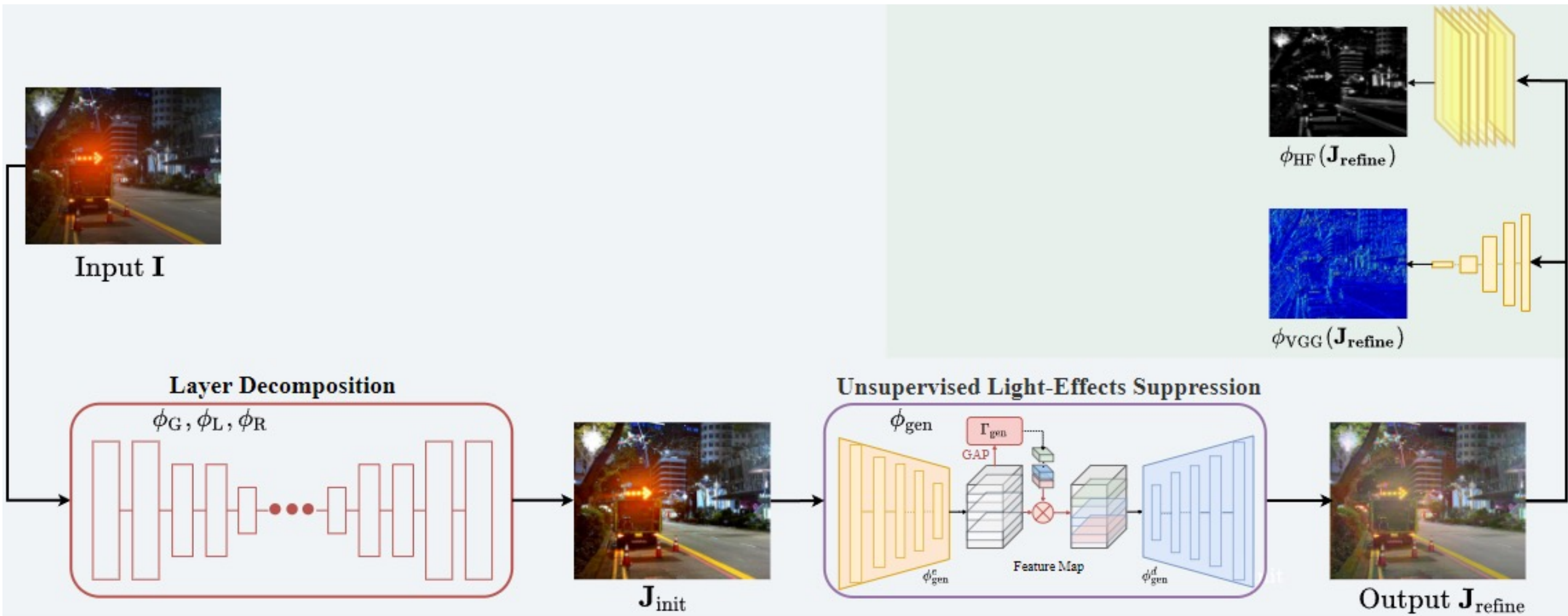
# Structure and HF-features Losses

$\Sigma$ : Weighted Sum

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

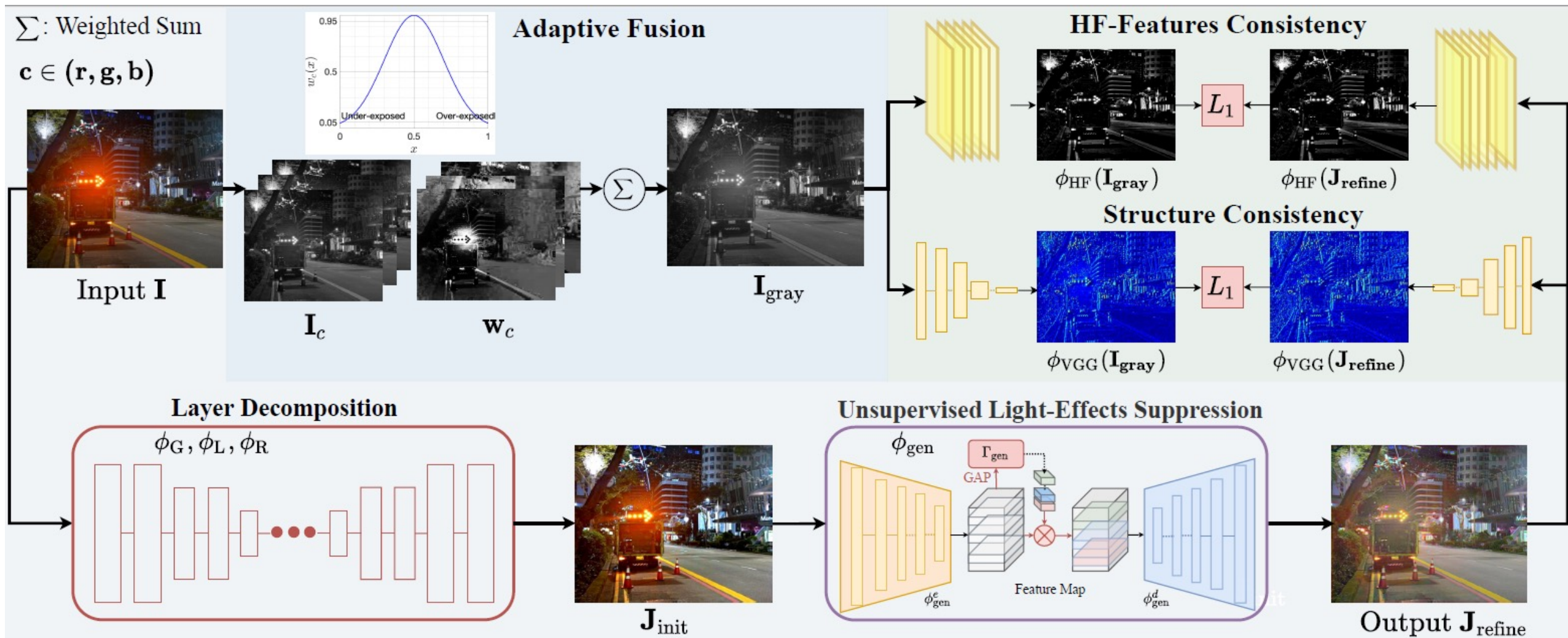


# Structure and HF-features Losses





# 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.

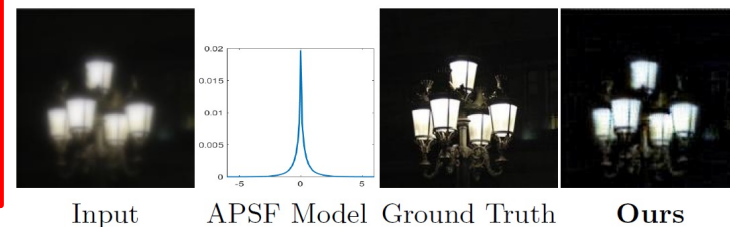
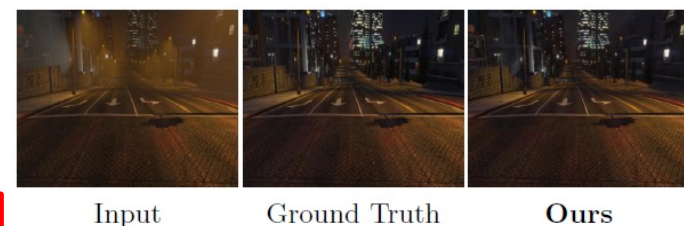
Three Aspects	EG [15]	Afi [1]	Yan [38]	Zhang [44]	Li [23]	Sharma [32]	Ours
1.Realism↑	$3.3 \pm 1.5$	$5.5 \pm 1.3$	$3.7 \pm 2.0$	$3.5 \pm 1.6$	$3.1 \pm 1.8$	$2.8 \pm 1.5$	<b><math>6.1 \pm 0.8</math></b>
2.L.E. Supp.↑	$1.7 \pm 0.8$	$3.1 \pm 1.3$	$4.6 \pm 1.4$	$3.9 \pm 1.1$	$5.2 \pm 1.2$	$3.0 \pm 1.5$	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

**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]	Afi [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	<b>29.79</b>
	SSIM↑	0.31	0.68	0.23	0.53	0.85	0.65	0.64	0.29	<b>0.88</b>
Syn-light-effects [27]	PSNR↑	7.38	7.84	6.39	11.31	14.88	16.30	14.66	14.00	<b>16.95</b>
	SSIM↑	0.17	0.20	0.16	0.35	0.23	0.38	0.37	0.37	<b>0.39</b>



# Results on Light-Effects Suppression



Input

Ours

Sharma [32]

EG [15]

Afifi [1]



# Results on Light-Effects Suppression

## ➤ Dark Zurich Dataset





# Results on Low-light Enhancement

Quantitative comparisons on the LOL-test dataset

Learning	Method	LOL-test			
		MSE( $\times 10^3$ ) $\downarrow$	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$
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	<b>0.198</b>
	Affi [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	<b>1.070</b>	<b>21.521</b>	<b>0.763</b>	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 $\uparrow$	9.72	17.33	17.34	17.34	11.43	12.67	14.85	20.54	15.33
SSIM $\uparrow$	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]	Affi [1]	DRBN [41]	EG [15]	Sharma [32]	Ours
PSNR $\uparrow$	17.56	15.47	13.27	19.40	16.38	19.66	18.23	18.34	<b>25.53</b>
SSIM $\uparrow$	0.54	0.56	0.45	0.69	0.53	0.76	0.61	0.64	<b>0.88</b>

# 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.



- With unsupervised structure and HF-features consistency loss, our method **restore the background details**.





---

# Thank you!

---

[JINYEYING@U.NUS.EDU](mailto:JINYEYING@U.NUS.EDU)

**CODES AND MODEL:**

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