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

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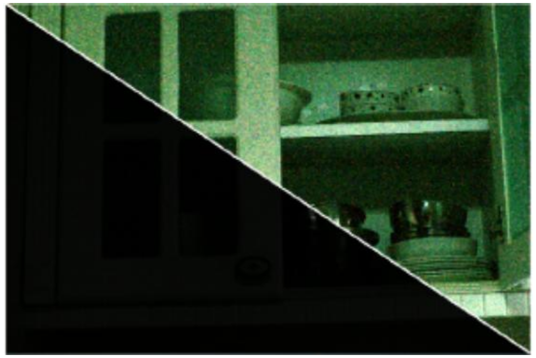
# 1.Introduction of Low Light Image Enhancement

**Background:**
High-level task are heavily dependent on the quality of the input images.
Insufficient light during capture can result in information loss and noise in the dark regions of the images.

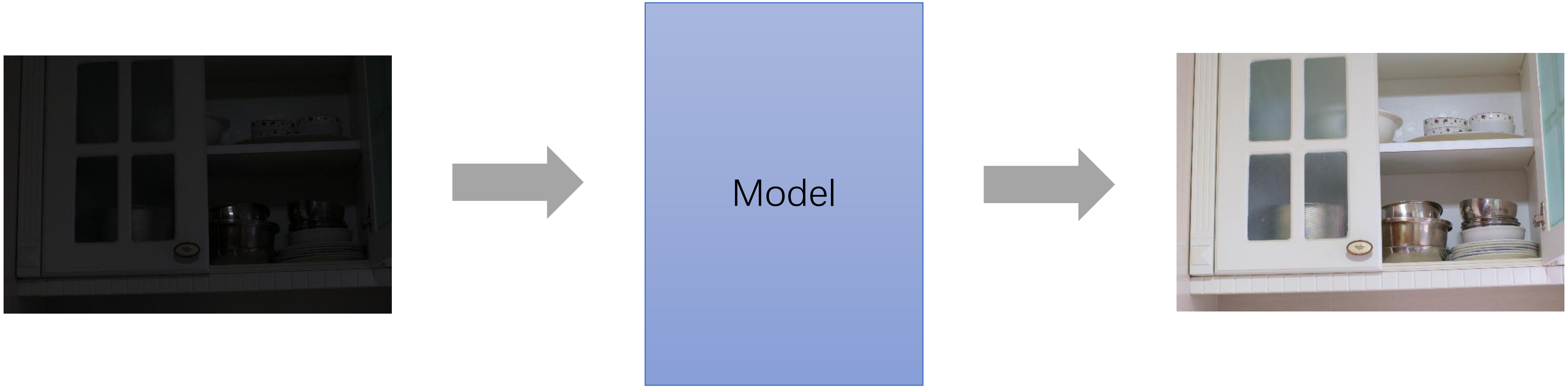
**Operations:**
Long exposure -> blur,    High ISO -> noise amplified,    Flash -> unbalanced lighting

**Challenge:**
When amplifying the intensity/brightness, noise also amplifies.
In low-light conditions, camera sensors are sensitive and non-linear to insufficient photons, which causes color distortion.



# 1.Introduction of Low Light Image Enhancement

Data driven method mostly uses **paired data** to train an enhancement model.




Powerful input:
- SNR map
- Light attention map
- Edge map
- Reflection map

……

Powerful model:
- Complex CNN
- Unet
- Transform
- GAN

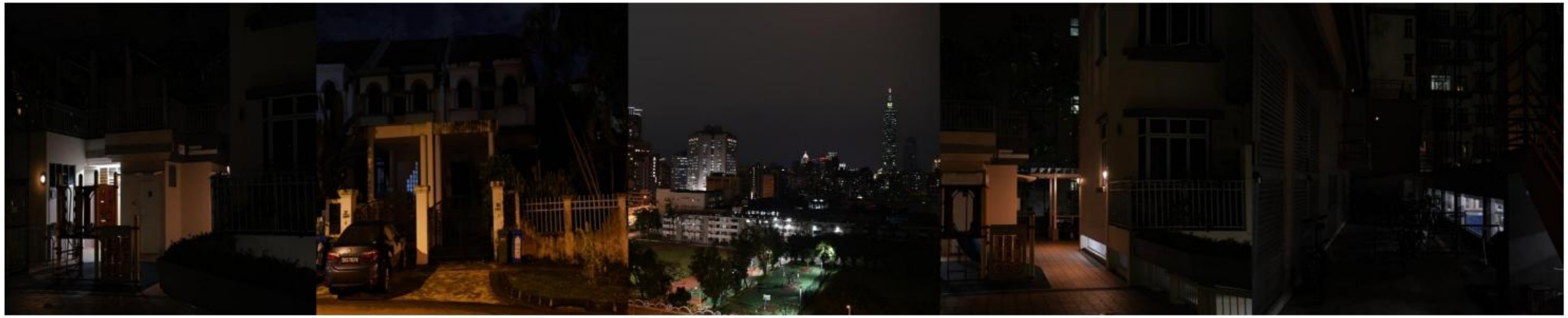
……

Powerful loss:
- MSE loss
- Color loss
- Light loss
- VGG loss

……

# 2.Motivation

➢Low Light:



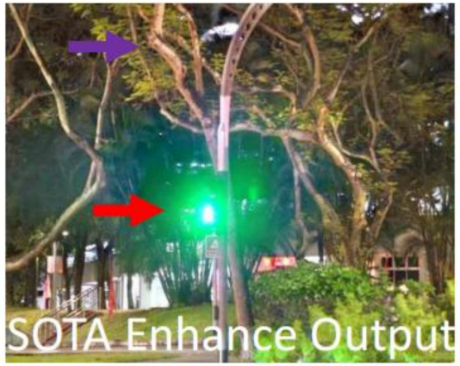
➢Light-Effects/Glare/Floodlight:

# 2.Motivation

➢ Existing low-light enhancement methods:


✓ Enhance low-light regions

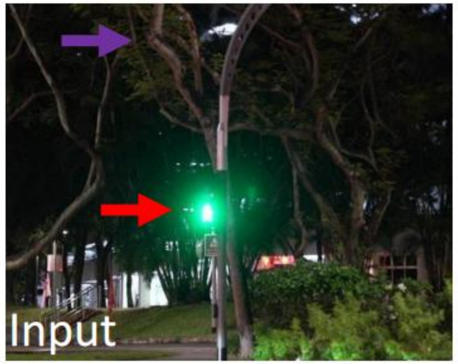
× Over-enhance light-effects regions




Low-light regions

Light-effects regions

➢ Existing night dehazing methods:



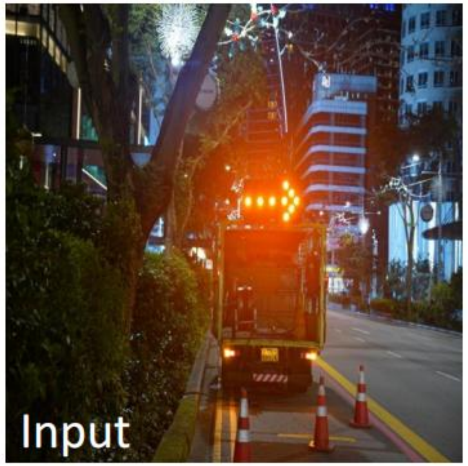

× Enhance low-light regions

✓ Suppress glow; × Suppress light-effects


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

# 3.Challenge

1. Lack of **paired** training data, hard to collect ground truth
2. Synthesizing physically correct night light-effects images is challenging


Solution: propose an *unsupervised* night image enhancement method.

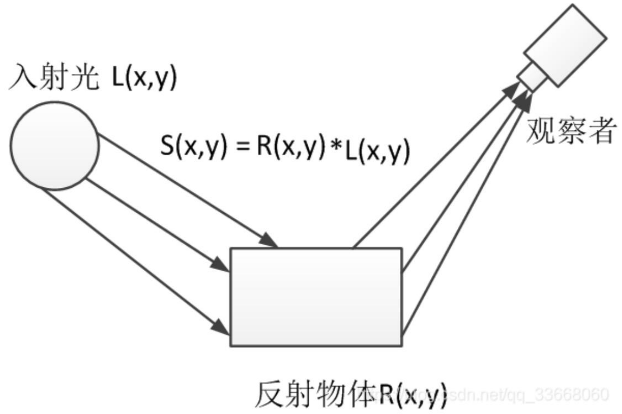
- Model-based Layer Decomposition
- Unpaired Light-Effects Suppression

# 4.Method Part1: Layer Decomposition

Our decomposition is based on the following image-layer model: $\mathbf{I} = \mathbf{R} \odot \mathbf{L} + \mathbf{G}$

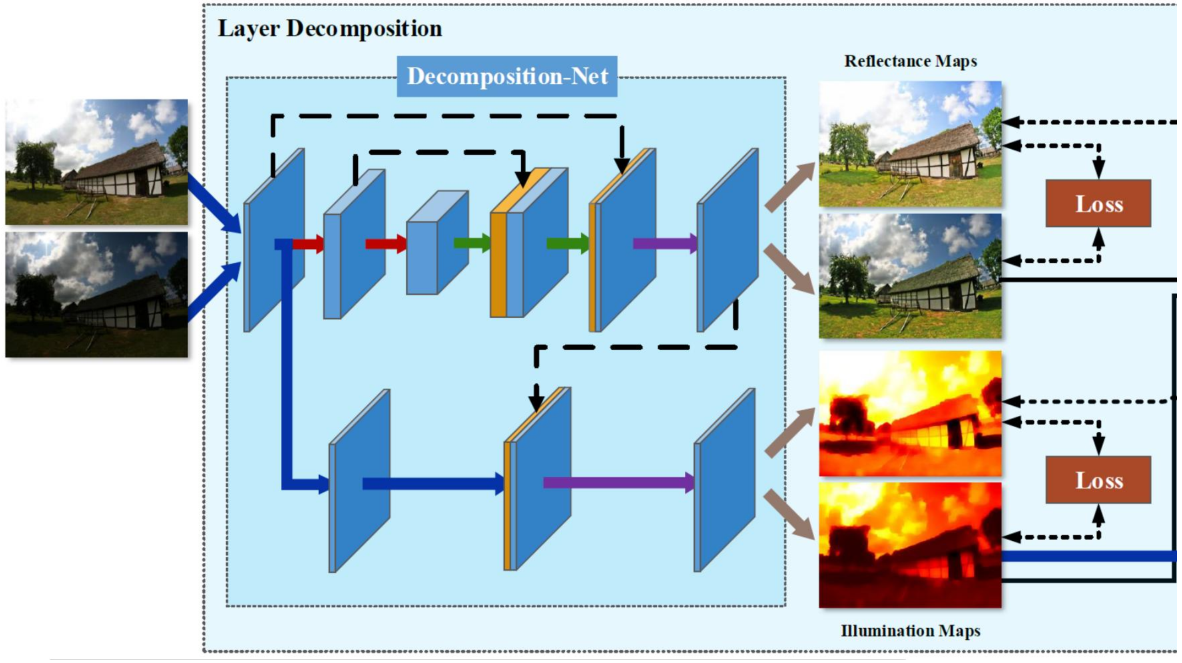
(a) Input $\mathbf{I}$ (b) $\mathbf{G}$ (c) $\mathbf{L}$ (d) $\mathbf{R}$

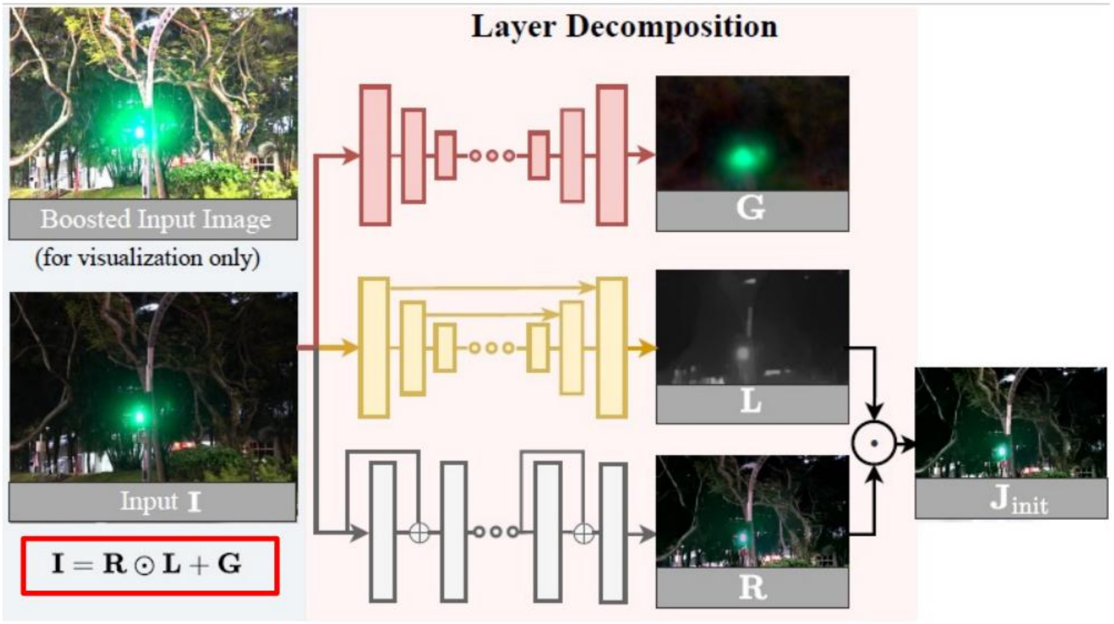
This idea is based on Retinex theory. It is a ill-posed question.



# 4.Method Part1: Layer Decomposition

Deep learning method based on Retinex theory (2019 ACMMM Kind)



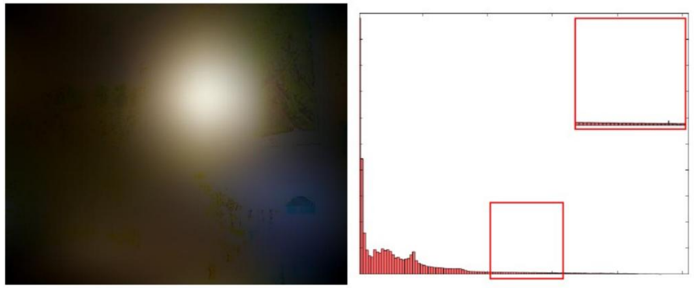
# 4.Method Part1: Layer Decomposition

## Four unsupervised loss:

(a) Input $\mathbf{I}$ (b) $\mathbf{G}$ (c) $\mathbf{L}$ (d) $\mathbf{R}$

*Light-Effects and Shading Initializa* $\mathcal{L}_{\text{init}} = |\mathbf{G} - \mathbf{G}_{\text{i}}|_1 + |\mathbf{L} - \mathbf{L}_{\text{i}}|_1 .$

$\mathrm{L_i}$ is max value of RGB channels. $G_{\mathrm{i}}$ is second-order Laplacian filter from the input image.



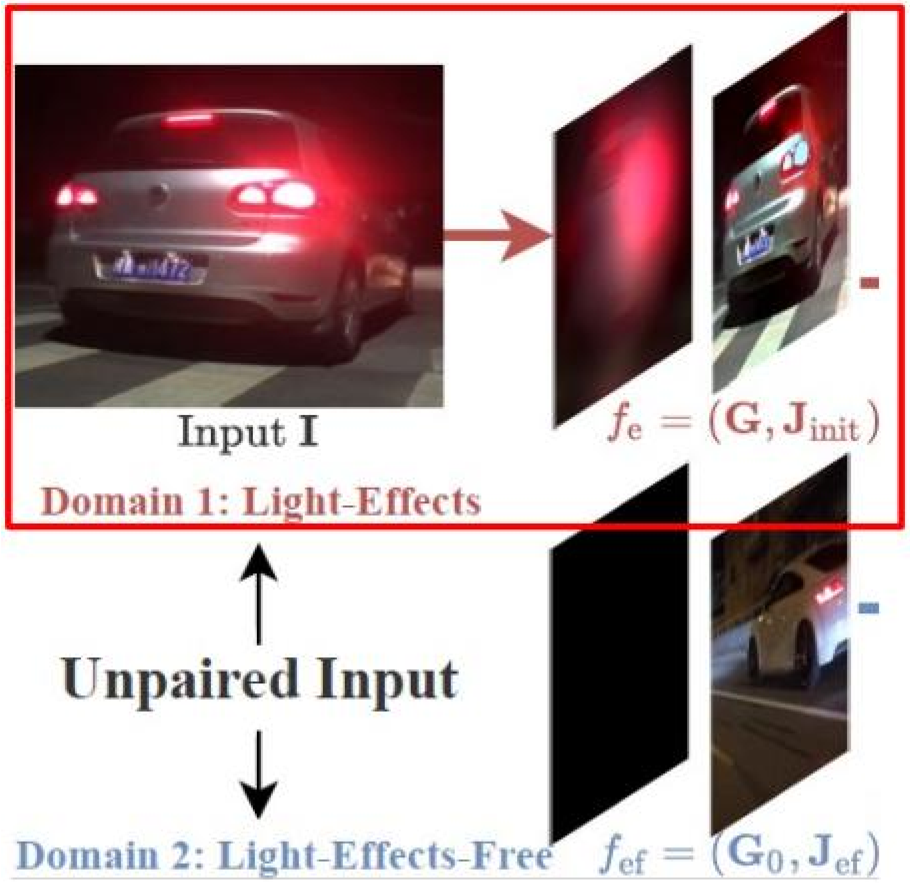
(b) Light-Effects Layer $\mathbf{G}$ (c) Gradient Histogram of $\mathbf{G}$

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

*Color Constancy Loss* $\mathcal{L}_{\text{cc}} = \sum_{(c1,c2)} (|\mathbf{J}_{\text{init}}^{c1} - \mathbf{J}_{\text{init}}^{c2}|_1),$ where $(\mathrm{c1}, \mathrm{c2}) \in \{(r,g),(r,b),(g,b)\}$

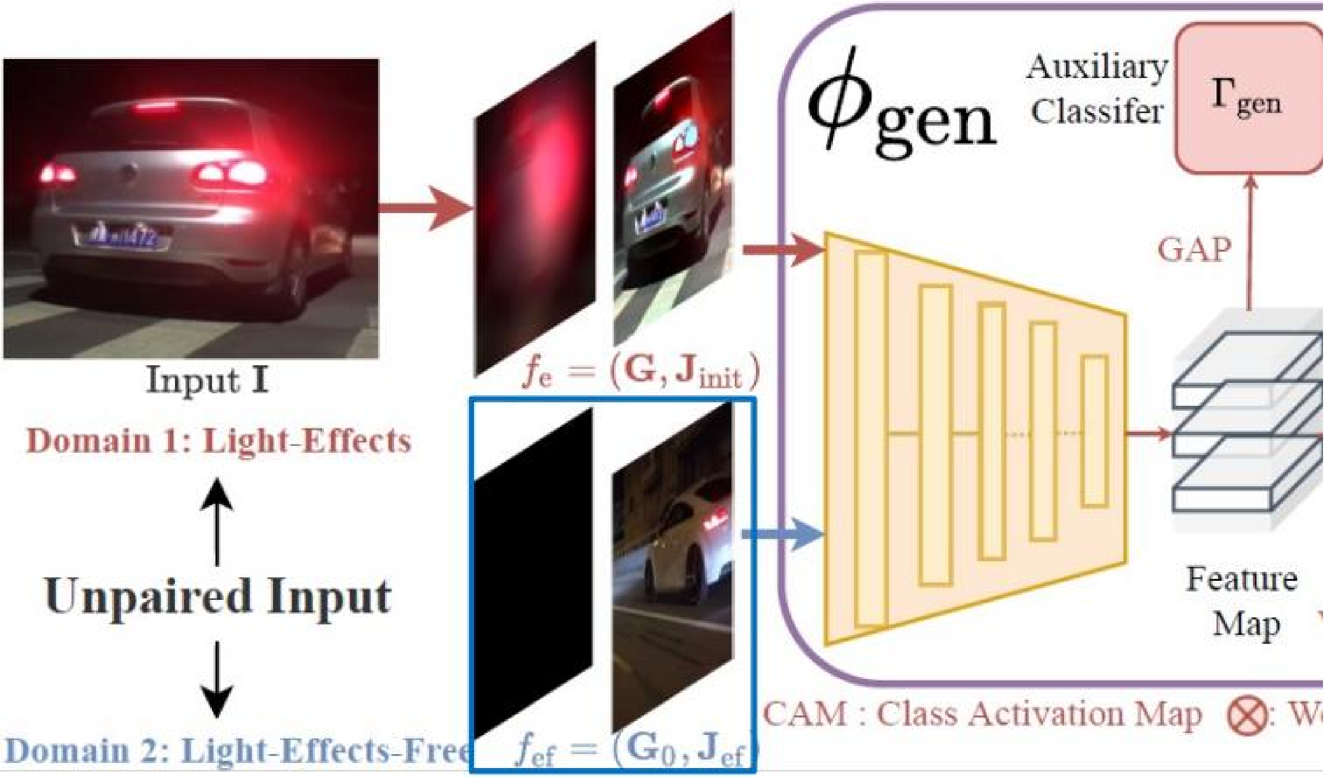
*Reconstruction Loss* $\mathcal{L}_{\text{recon}} = |\mathbf{I} - (\mathbf{R} \odot \mathbf{L} + \mathbf{G})|_1 .$

# 4.Method Part2: Light-effects Suppression



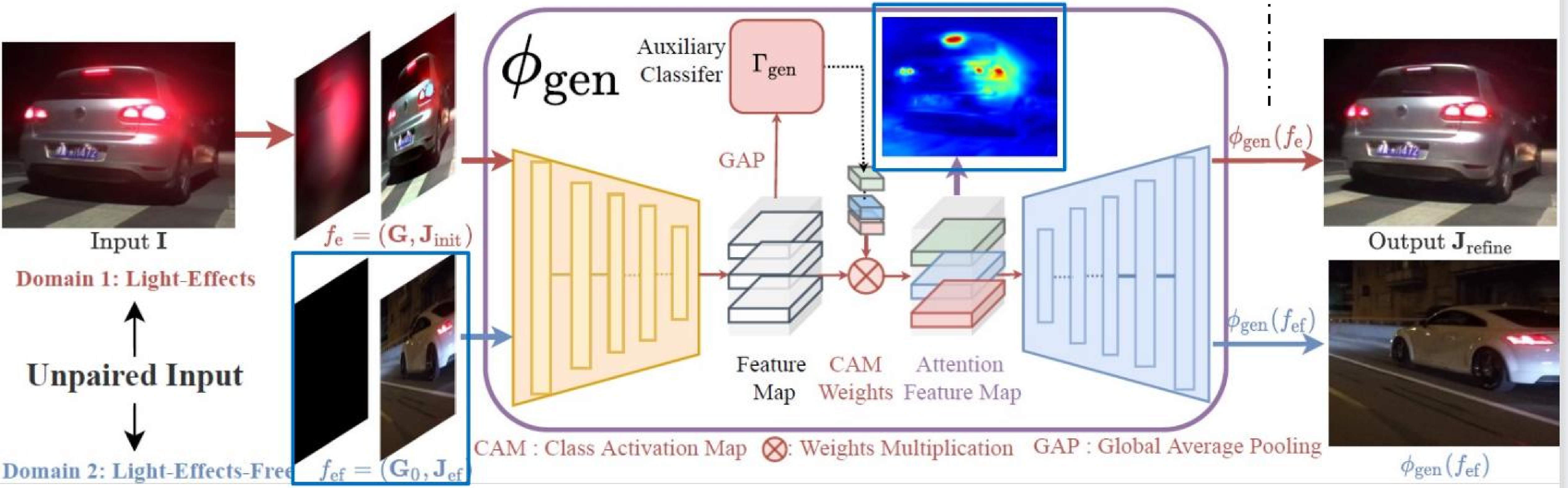
# 4.Method Part2: Light-effects Suppression

$$\mathcal{L}_{\text{atten}} = -\left(\mathbb{E}\left[\log(\Gamma_{\text{gen}}(f_{\text{e}}))\right] + \mathbb{E}\left[\log(1 - \Gamma_{\text{gen}}(f_{\text{ef}}))\right]\right).$$

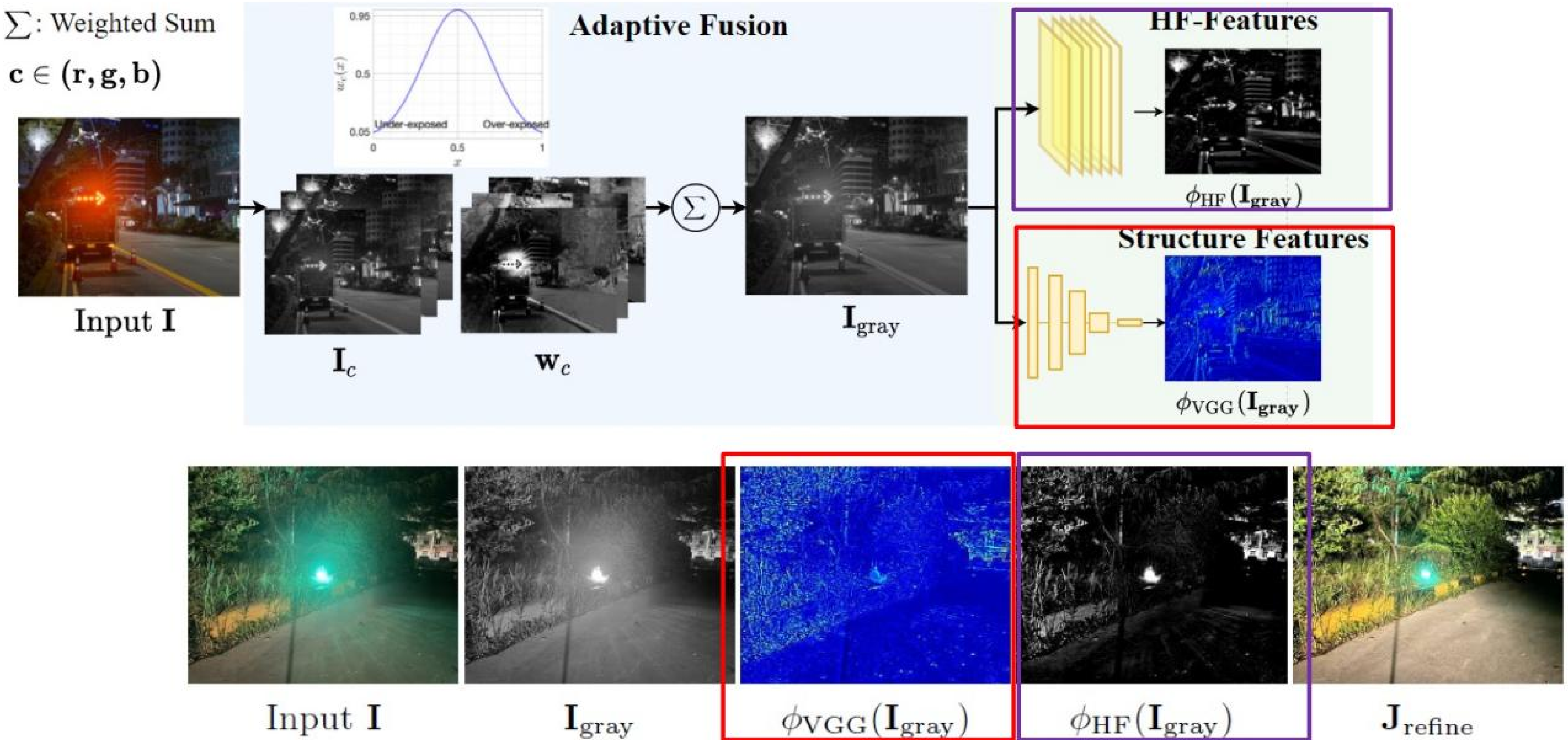


# 4.Method Part2: Light-effects Suppression

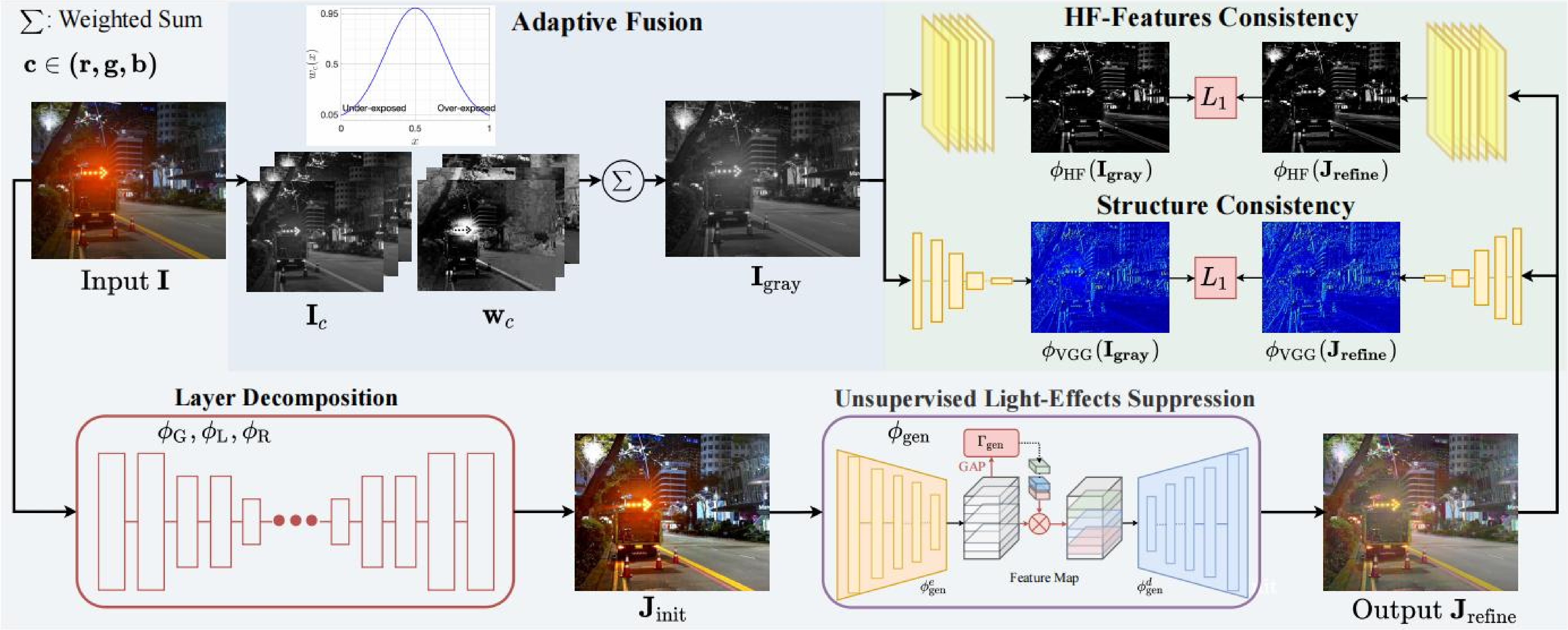
$$\mathcal{L}_{adv} = \mathbb{E}\left[\log\left(\phi_{dis}(\mathbf{J}_{ef})\right)\right] + \mathbb{E}\left[\log\left(1-\phi_{dis}(\mathbf{J}_{refine})\right)\right].$$



# 4.Method Part3: Structure and HF-features Losses



# 4.Method Part3: Structure and HF-features Losses



# 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 | **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$\uparrow$ | 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] | Afifi [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 | **25.53** |
| SSIM$\uparrow$ | 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/ $\mathcal{L}_{\text{gray-feat}}$