## **Brighten-and-Colorize: A Decoupled Network for Customized Low-Light Image Enhancement**

ACM MM 2023

# Introduction



Recent advances mainly focus on the refinement of the lightness, while **ignoring the role of chrominance**. It easily leads to **chromatic aberration or artifacts**.





MIRNet-v2 (TPAMI 2022)



GT

# Introduction

Image Colorization  $\longrightarrow$  Low-light Image Color Recover

Key challenges:

- How to ensure boundaries of the generated chrominance?
  semantic information
- How to solve the problem that one object can be filled by multiple colors ?

color strokes, reference image

Although the chrominance of low-light image is unsaturated, it contains both boundary information and some color hints.

low-light chrominance as a guidance to recover proper colors. ——— customized enhancement

- customized saturation
- customized color style

LLIE is decoupled into the **brightening** and **colorization** sub-tasks.

### Framework



# Brightening

![](_page_4_Figure_1.jpeg)

![](_page_4_Figure_2.jpeg)

Lightness Adjustment Module

 $F_{L} = Encoder(L_{in})$  $B = 1 - L_{in}, E = edge(L_{in})$  $F_{out} = F_{in} \times \psi(B) \times (1 + \psi(E))$ 

$$\mathcal{L}_{rec-l} = \sqrt{\left\|L_{actual} - L_{pred}\right\|_2} + \epsilon^2$$

# Colorization

![](_page_5_Figure_1.jpeg)

![](_page_5_Figure_2.jpeg)

Color Embedding Module

 $\hat{F_{in}} = F_{in-l} + F_{in-c}$ 

$$A_l = sigmoid(conv_l(\hat{F_{in}})) \quad A_c = sigmoid(conv_c(\hat{F_{in}}))$$

$$F_{out} = F_{in-l} \times A_l + F_{in-c} \times A_c$$

$$\mathcal{L}_{rec-c} = \left\| C_{actual} - C_{pred} \right\|_{1}$$

# Colorization

![](_page_6_Figure_1.jpeg)

![](_page_6_Figure_2.jpeg)

Figure 3: The quantization operation [48] in CIELAB color space. The continuous colors (left) are quantized to 313 discrete colors (right) with a grid size of 10.

Color Classification Loss

$$\mathcal{L}_{q} = \mathcal{H}(q_{actual}, q_{pred})$$
$$= -\sum_{h,w} \sum_{p} q_{actua} \sum_{h,w,p} \log(q_{pred_{h,w,p}})$$

$$q_{pred} \in \mathbb{R}^{h \times w \times 313}$$

# Customized Enhancement

![](_page_7_Figure_1.jpeg)

Saturation Control

 $C_{in} \times (1 + \omega)$ 

Color Style Control.

 $(1 - \gamma) \times F_c + \gamma \times F'_c$ 

#### Color Adaptation

![](_page_7_Picture_7.jpeg)

$$L_{in}, a_{in}, b_{in} = RGB2Lab(I_{in})$$
$$L_{ref}, a_{ref}, b_{ref} = RGB2Lab(I_{ref})$$

$$\begin{aligned} a_{in} &= a_{in} - mean(a_{in}), b_{in} = b_{in} - mean(b_{in}) \\ a_{in} &= a_{in} \times (std(a_{in})/std(a_{ref})) \\ b_{in} &= b_{in} \times (std(b_{in})/std(b_{ref})) \end{aligned}$$

$$C_{ref-in} = cat(a_{in}, b_{in})$$

## **Experiments**

Table 1: Quantitative comparison on the LOL-real [43] and FiveK [1]. The best results are boldfaced and the second-best ones are underlined.

Methods			LOL-real	[43]				FiveK [	1]		Size (M)
methodb	PSNR ↑	SSIM ↑	$\Delta E\_ab\downarrow$	LPIPS ↓	CSE (ratio)↓	PSNR ↑	SSIM ↑	$\Delta E\_ab \downarrow$	LPIPS ↓	CSE (ratio) ↓	
DRD[39]	16.08	0.6555	22.35	0.2364	2.53	21.68	0.8604	10.52	0.0574	2.18	0.86
Kind[52]	20.01	0.8412	12.53	0.0813	1.30	20.71	0.8835	10.75	0.0480	1.38	8.02
Kind++[51]	20.59	0.8294	12.51	0.0875	1.18	19.71	0.8640	14.05	0.0574	2.12	8.27
MIRNet[46]	22.11	0.7942	10.11	0.1448	1.35	24.41	0.9097	7.90	0.0344	1.33	31.79
EnGAN[8]	18.64	0.6767	17.73	0.1512	6.18	15.38	0.7752	18.89	0.0984	2.97	8.64
DeepUPE[37]	18.68	0.5791	17.54	0.1868	9.48	24.24	0.8957	8.16	0.0440	2.15	0.99
DeepLPF[25]	20.03	0.7819	12.58	0.1460	3.23	24.74	0.9170	7.50	0.0570	1.44	1.72
UEGAN[26]	20.30	0.7417	14.69	0.1464	12.97	23.00	0.8717	9.96	0.0503	3.84	4.16
SGM[43]	20.06	0.8158	11.36	0.0727	1.33	22.57	0.8823	9.36	0.0557	4.23	2.31
MIRNet-v2[45]	21.83	0.8455	11.47	0.0666	1.49	25.04	0.9188	8.05	0.0357	1.54	5.86
SNR-Aware[41]	21. <mark>4</mark> 8	0.8478	10.58	0.0740	1.14	25.41	0.9234	7.24	0.0293	1.49	39.12
Ours	23.27	0.8637	8.97	0.0566	1.00	25.74	0.9285	6.77	0.0291	1.00	6.84

#### $\triangle E\_ab : L2\_distance$ in CIELab color space

CSE: Color Sensitive Error

## • Experiments

![](_page_9_Picture_1.jpeg)

Figure 8: The qualitative comparison on FiveK [1] (the first row) and LOL-real [43] (the second row). It can be seen that the proposed method reaches the best visual results.

![](_page_9_Picture_3.jpeg)

## Experiments

![](_page_10_Figure_1.jpeg)

Table 2: Quantitative comparison with two-step "brightenand-colorize" methods on LOL-real [43] dataset. The best results are boldfaced and the second-best ones are underlined. Note that "\*" represents this method is retrained.

Brightener	Colorizer	PSNR ↑	SSIM ↑	$CSE(ratio) \downarrow$
	Zhang <i>et al.</i> * [50]	20.90	0.8304	1.34
SNR-Aware [41]	Zhang et al. [50]	11.81	0.5411	70.44
	Yin et al. [44]	19.69	0.7881	7.40
	Zhang <i>et al.</i> * [50]	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	0.8242	1.09
MIRNet-v2 [45]	Zhang et al. [50]	12.01	0.5313	77.60
	Yin et al. [44]	20.44	0.7810	7.30
0	urs	23.27	0.8637	1.00

![](_page_10_Figure_4.jpeg)

Figure 9: The qualitative comparison with "brighten-andcolorize" methods. Note that two brighteners have similar visual results, we only present the results of SNR-Aware [41].

## **Experiments**

Table 3: Ablation studies on LOL-real [43] dataset. The best results are boldfaced and the second-best ones are underlined.

Methods	PSNR ↑	SSIM ↑	CSE(ratio)↓	Size (M)
W/o Decoupling	21.28	0.8003	3.05	4.22
W/o Sharing	23.03	0.8591	1.12	8.44
W/o LAM	22.77	0.8516	0.91	6.84
W/o CEM	23.06	0.8575	1.66	6.84
W/o $\mathcal{L}_q$	23.21	0.8600	1.11	6.84
Ours	23.27	0.8637	1.00	6.84

![](_page_11_Picture_3.jpeg)

Figure 10: The qualitative comparison of ablation studies.

Table 6: Results of the color space ablation studies on LOLreal [43] dataset. The best results are boldfaced and the second-best ones are underlined.

Methods	PSNR	SSIM	LPIPS	CSE (ratio)
HSV	22.02	0.8257	0.0809	1.12
HLS	22.31	0.8454	0.0869	1.38
Luv	22.02	0.8420	0.0702	1.06
Yuv	22.37	0.8416	0.0751	1.16
Lab (ours)	23.21	0.8600	0.0619	1.00

# Thanks!