Learning to Enhance Low-Light Image via Zero-Reference Deep Curve Estimation

Chongyi Li

April 23, 2021

Learning to Enhance Low-Light Image via Zero-Reference Deep Curve Estimation, TPAMI, 2021
Zero-Reference Deep Curve Estimation for Low-Light Image Enhancement, CVPR, 2020
https://li-chongyi.github.io/Proj_Zero-DCE++.html

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Outline

- Part 1 – Background
- Part 2 – Zero-DCE
- Part 3 – Zero-DCE++
- Part 4 – Experiments
- Part 5 – Related Work

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Part 1: Background

Low-Light Enhancement

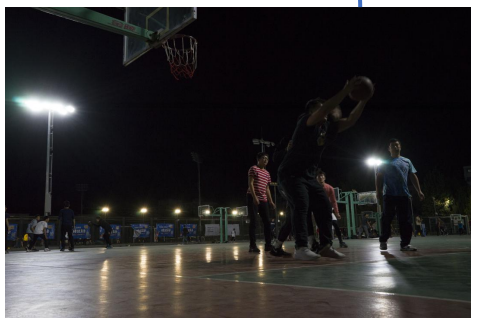
Under-Exposure

Low Light

Applications

Detection and Recognition in the Dark

face



car

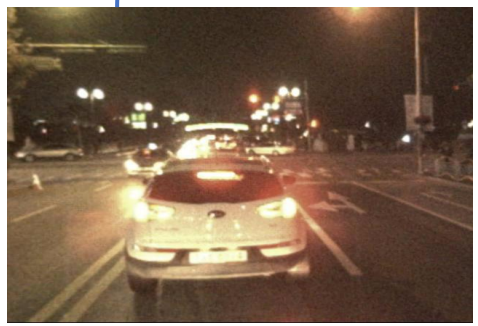


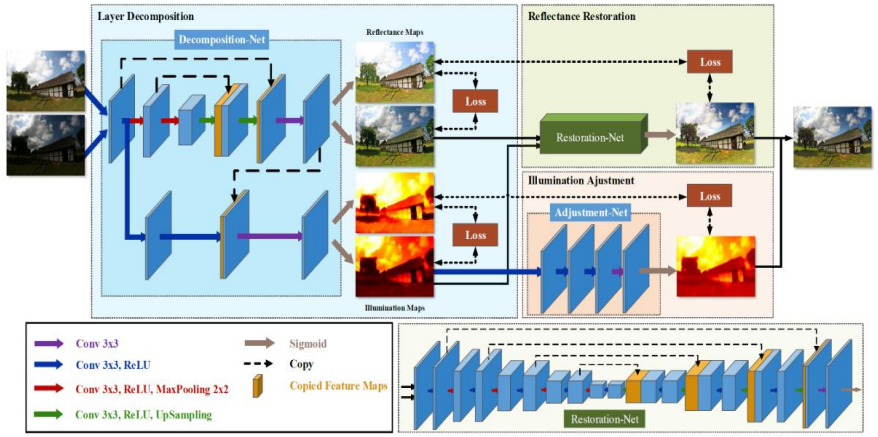
Photo Auto Editing

NORMAL VIEW

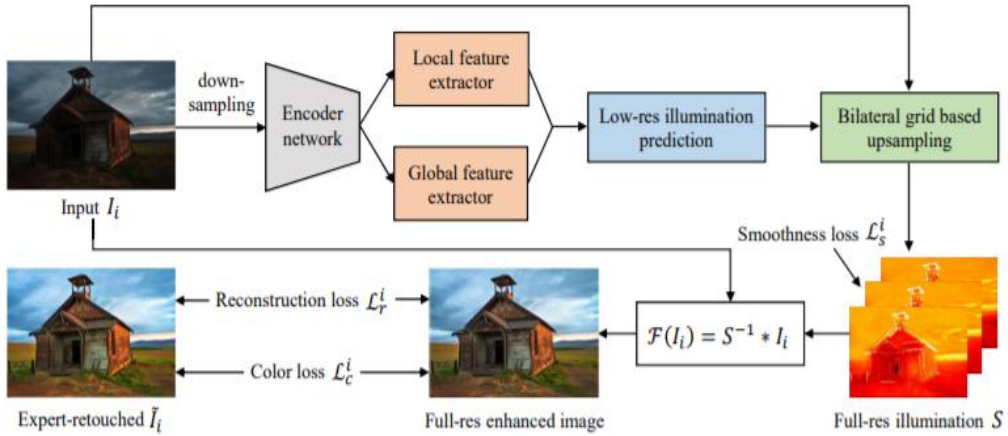
HUAWEI P30 PRO

see the unsee in the dark

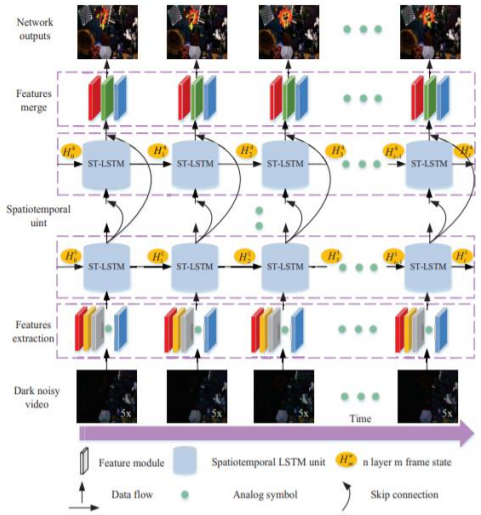
Network Structures



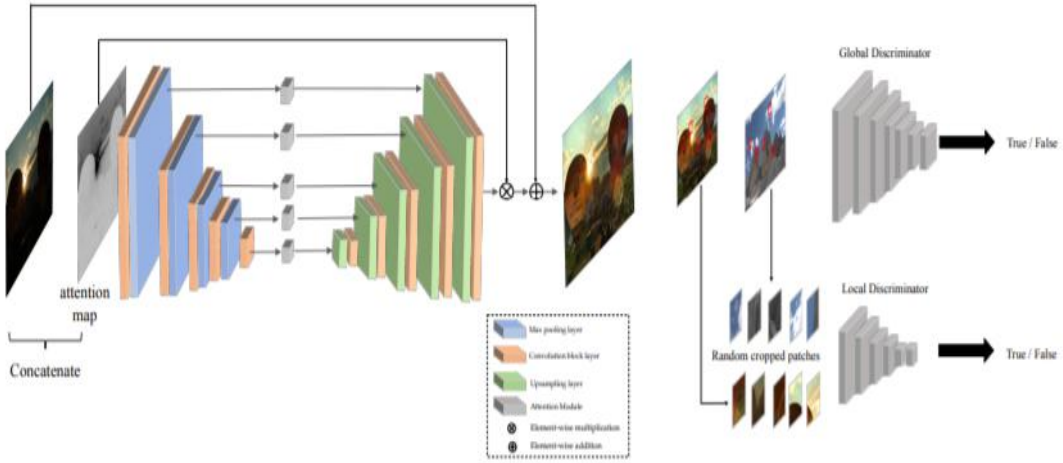
Zhang et al. ACMMM19



Wang et al. CVPR19



Wang et al. ICCV19

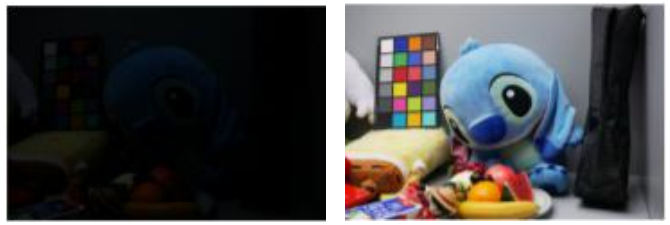


Jiang et al. TIP21

Training Data

Paired Training Data:

Retouching



Altering Exposure Time

Simulating

Unpaired Training Data:

Source

Target

Limitations

- ***Inefficient***: Require complex network structures

  --> **high computational burden**

- ***Sensitive***: Rely on either synthesized or corrupted and clean image pairs

  --> **visually unpleasing results**

- ***Inflexible***: Require careful selection of unpaired data and complex training

  --> **time-consuming training & hard to re-implement**

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Part 2: Zero-DCE

Zero-DCE

Zero-DCE

- We propose a low-light enhancement network that is independent of paired and unpaired training data

  --> **avoid the risk of overfitting & generalize well to various lighting conditions**

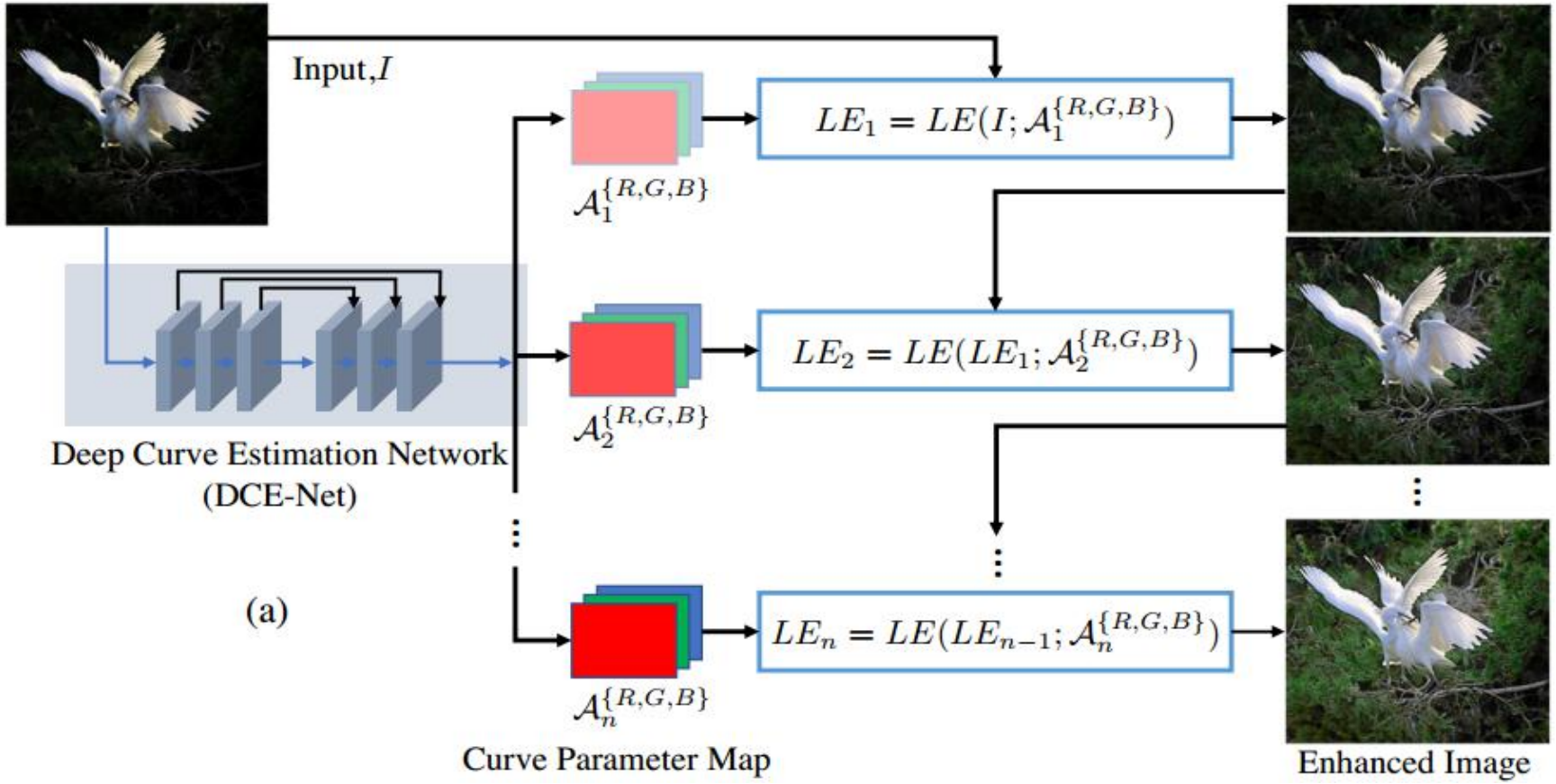
- We design an image-specific curve that is able to approximate pixel-wise and high-order curves by iteratively applying itself

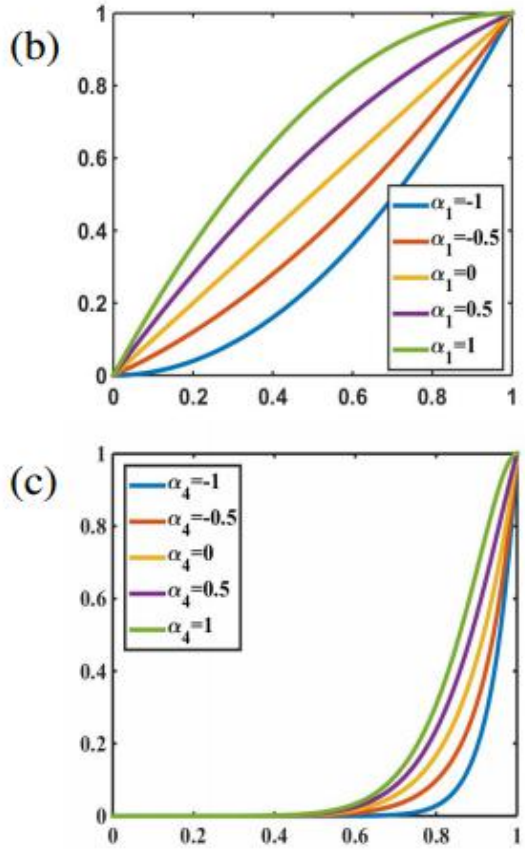
  --> **perform mapping within a wide dynamic range**

- We devise task-specific non-reference loss functions that indirectly evaluate enhancement quality

  --> **show the potential of training a deep model in the absence of reference images**

Zero-DCE

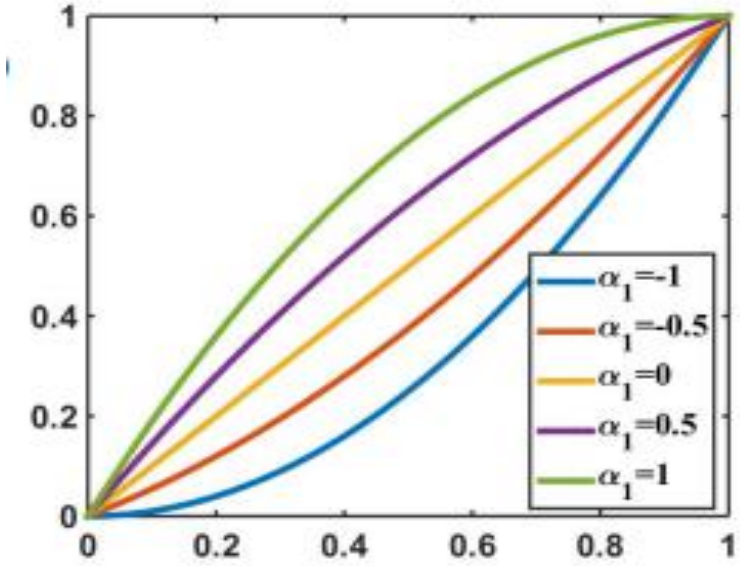

Input, I
$LE_1 = LE(I; \mathcal{A}_1^{\{R,G,B\}})$
$\mathcal{A}_1^{\{R,G,B\}}$
$LE_2 = LE(LE_1; \mathcal{A}_2^{\{R,G,B\}})$
$\mathcal{A}_2^{\{R,G,B\}}$
$LE_n = LE(LE_{n-1}; \mathcal{A}_n^{\{R,G,B\}})$
$\mathcal{A}_n^{\{R,G,B\}}$
Deep Curve Estimation Network
(DCE-Net)
(a)
Curve Parameter Map
Enhanced Image


(b)
α_1=-1
α_1=-0.5
α_1=0
α_1=0.5
α_1=1
(c)
α_4=-1
α_4=-0.5
α_4=0
α_4=0.5
α_4=1

Light-Enhancement Curves (LE-Curves)

$$LE(I(\mathbf{x});\alpha) = I(\mathbf{x}) + \alpha I(\mathbf{x})(1 - I(\mathbf{x}))$$

enhanced low-light trainable curve parameter [-1, 1]



LE-Curves

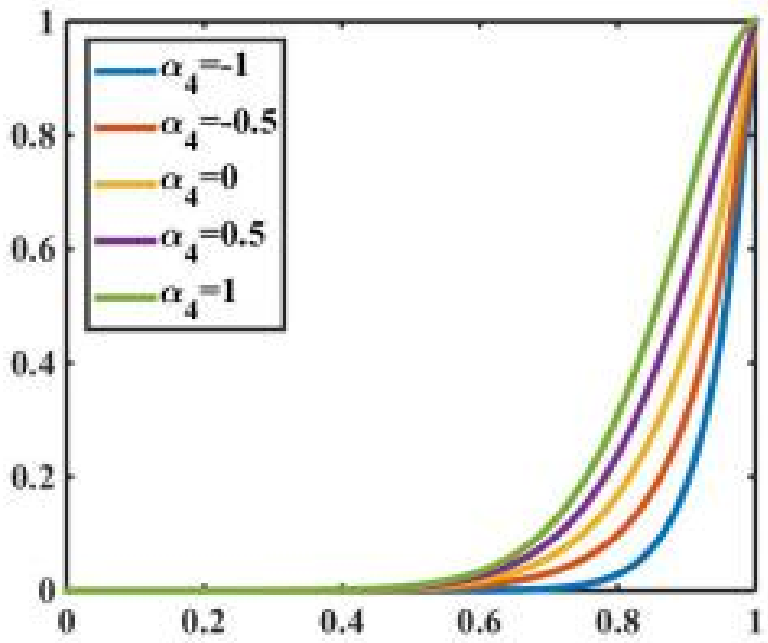
High-Order LE-Curves

$$LE_n(\mathbf{x}) = LE_{n-1}(\mathbf{x}) + \alpha_n LE_{n-1}(\mathbf{x})(1 - LE_{n-1}(\mathbf{x}))$$

the number of iteration

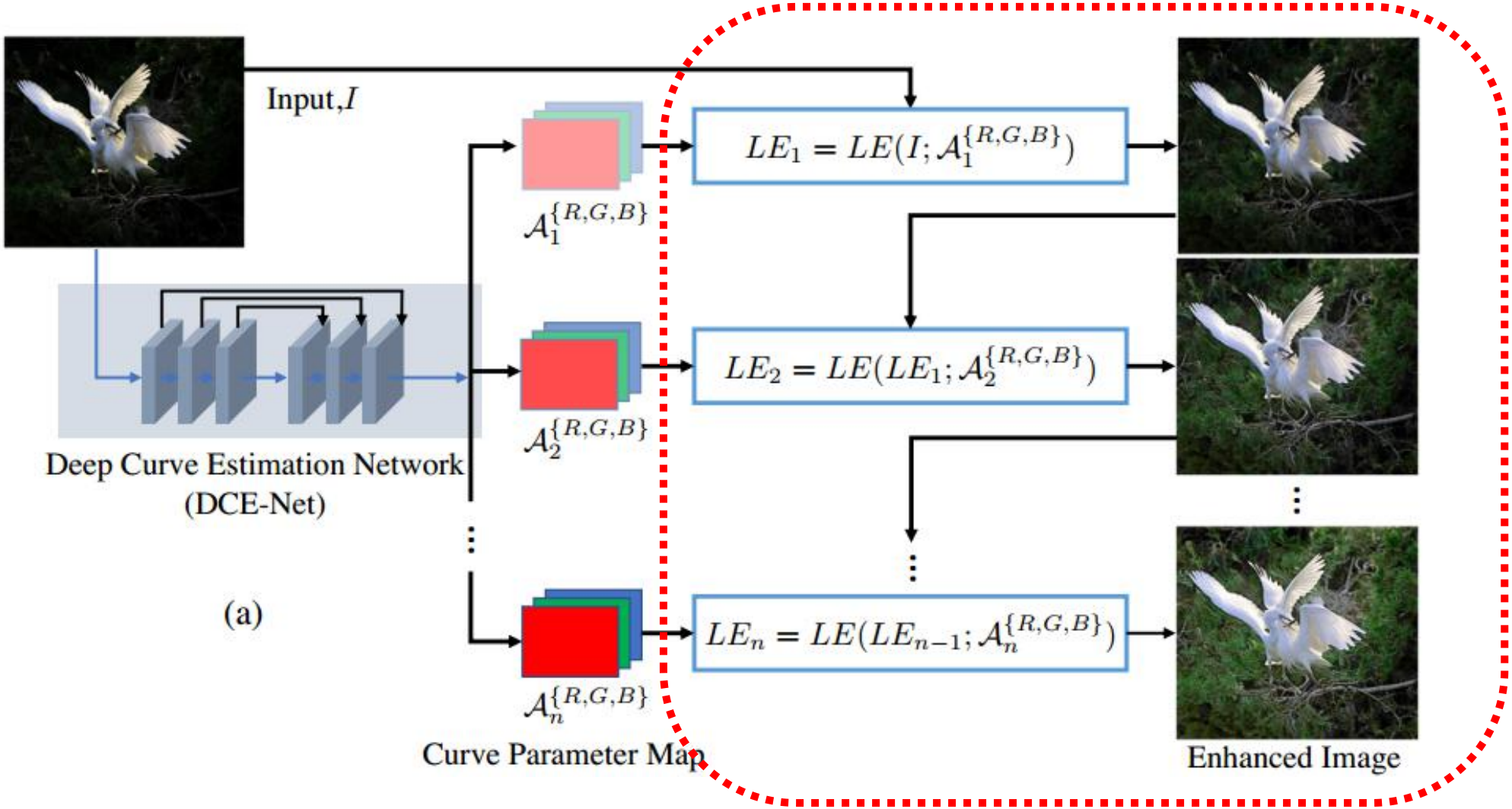
n=1

$$LE(I(\mathbf{x}); \alpha) = I(\mathbf{x}) + \alpha I(\mathbf{x})(1 - I(\mathbf{x}))$$



High-Order LE-Curves

High-Order LE-Curves

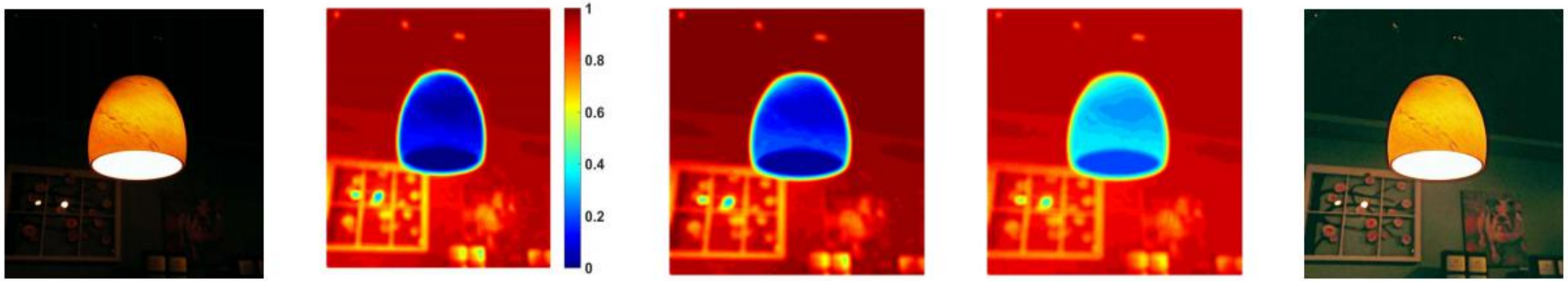


Pixel-Wise High-Order LE-Curves

$$LE_n(\mathbf{x}) = LE_{n-1}(\mathbf{x}) + \alpha_n LE_{n-1}(\mathbf{x})(1 - LE_{n-1}(\mathbf{x}))$$

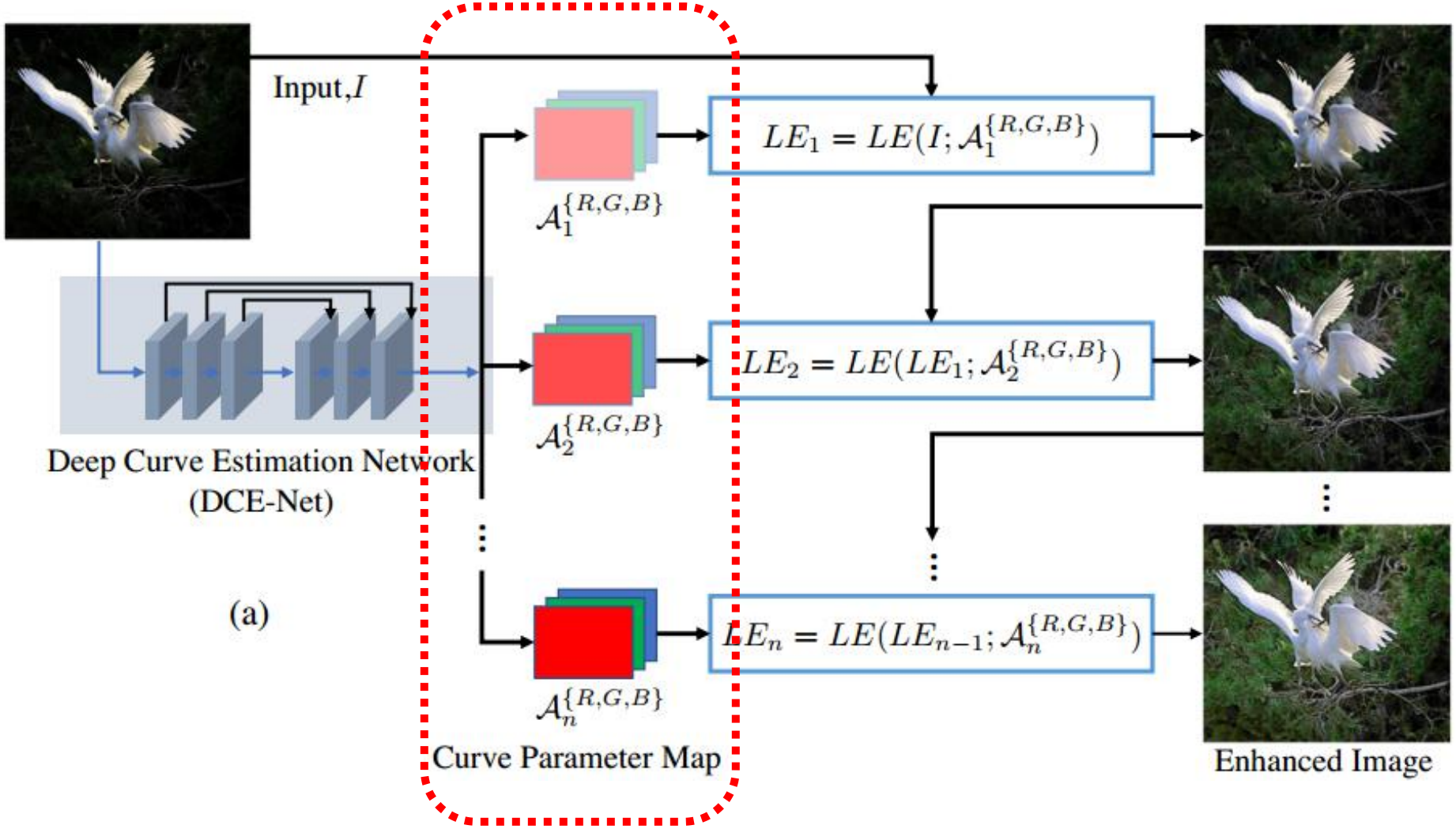
$$LE_n(\mathbf{x}) = LE_{n-1}(\mathbf{x}) + \mathcal{A}_n(\mathbf{x}) LE_{n-1}(\mathbf{x})(1 - LE_{n-1}(\mathbf{x}))$$

parameter map with the same size as the given image

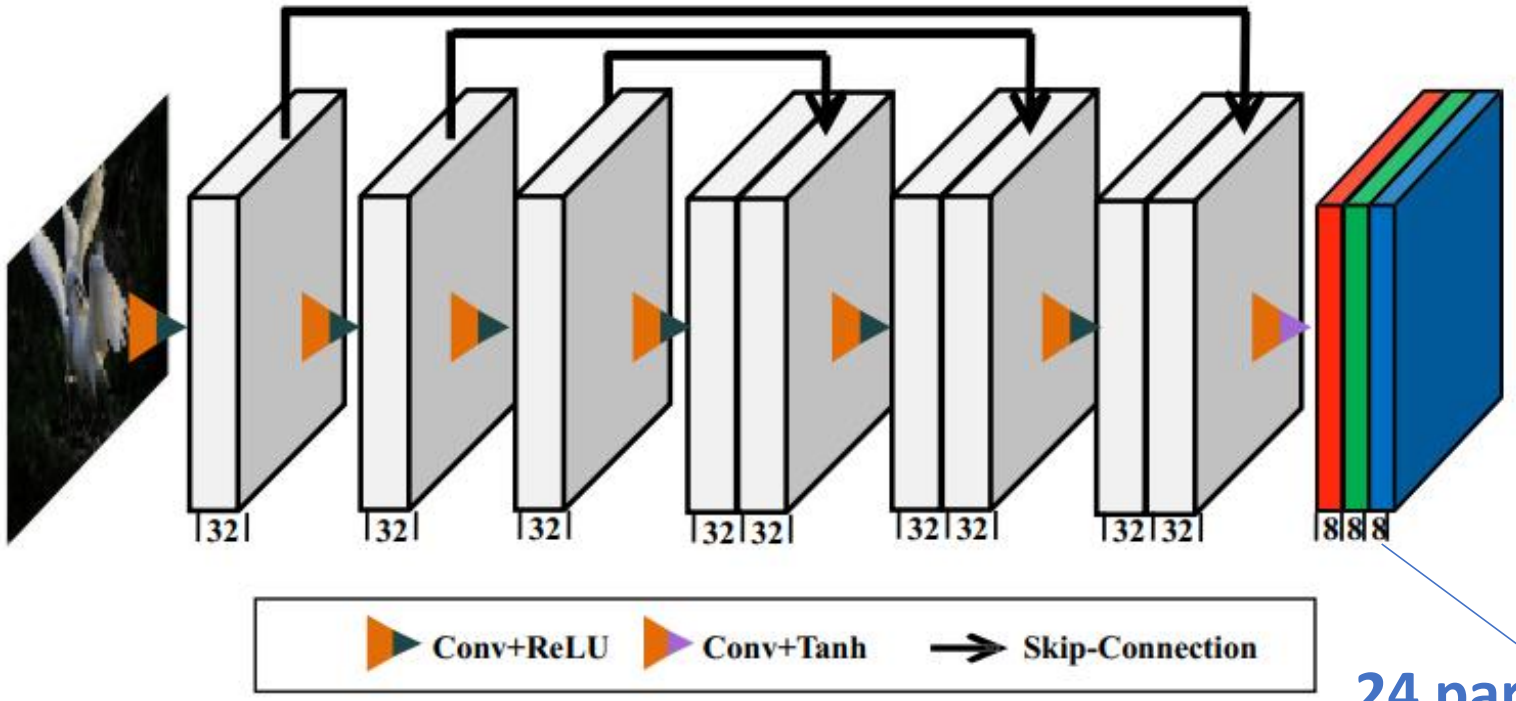


(a) Input (b) $\mathcal{A}_n^R$ (c) $\mathcal{A}_n^G$ (d) $\mathcal{A}_n^B$ (e) Result

Pixel-Wise High-Order LE-Curves



Deep Curve Estimation Network (DCE-Net)



24 parameter maps for 8 iterations

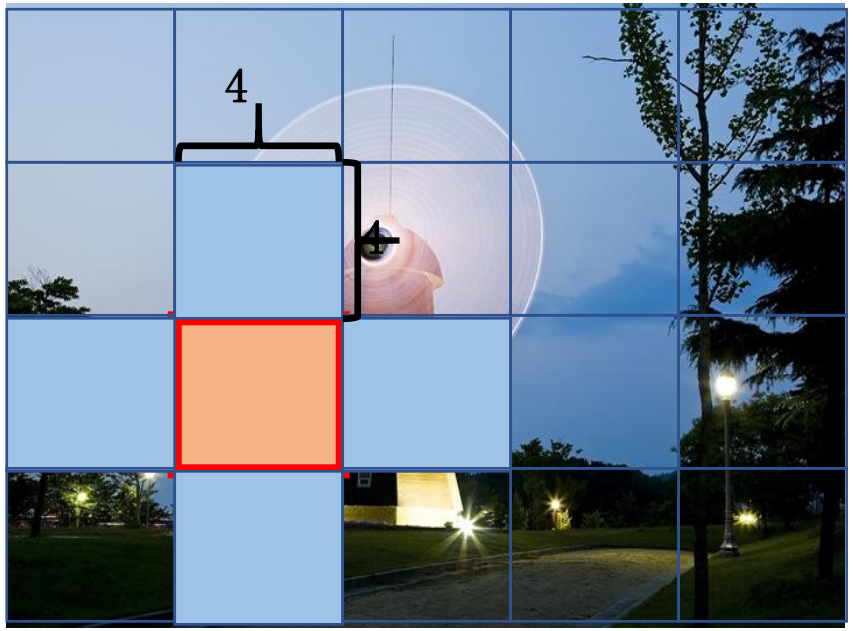
DCE-Net: 79,416 trainable parameters, and 5.21G FLOPs for an input image of size 256×256

Non-Reference Loss Functions

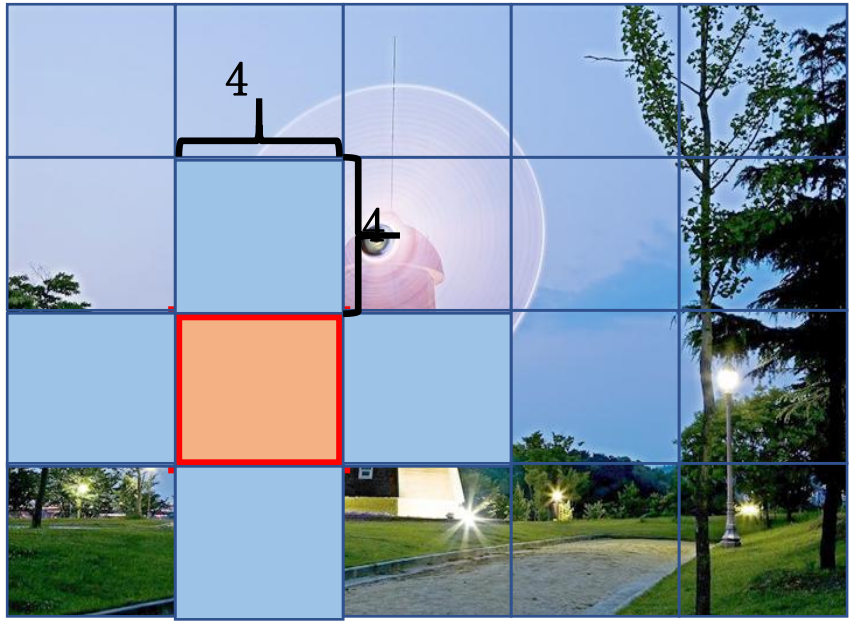
- Spatial Consistency Loss
- Exposure Control Loss
- Color Constancy Loss
- Illumination Smoothness Loss

Spatial Consistency Loss

$$L_{spa} = \frac{1}{K} \sum_{i=1}^{K} \sum_{j \in \Omega(i)} (|(Y_i - Y_j)| - |(I_i - I_j)|)^2$$



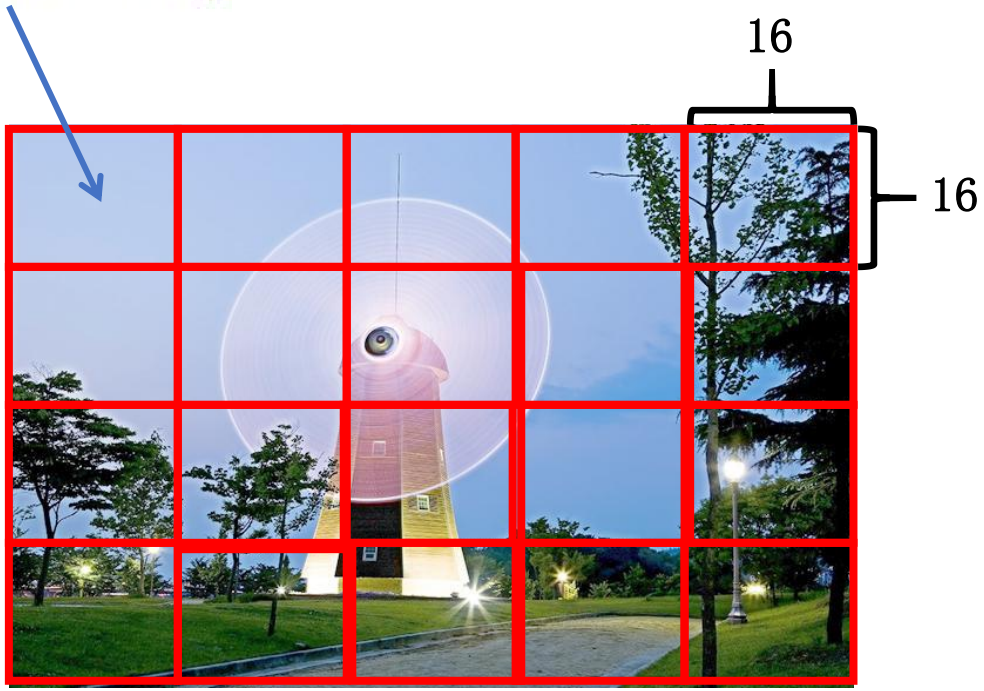
low-light



enhanced

Exposure Control Loss

$$L_{exp} = \frac{1}{M} \sum_{k=1}^{M} |Y_k - E|$$



enhanced

Color Constancy Loss

$$L_{col} = \sum_{\forall(p,q)\in\varepsilon} (J^p - J^q)^2, \varepsilon = \{(R,G),(R,B),(G,B)\}$$

Illumination Smoothness Loss

$$L_{tv_{\mathcal{A}}} = \frac{1}{N}\sum_{n=1}^{N}\sum_{c\in\xi}(|\nabla_x \mathcal{A}_n^c| + \nabla_y \mathcal{A}_n^c|)^2, \xi = \{R, G, B\}$$

(a) Input (b) Zero-DCE (c) w/o L_{spa} (d) w/o L_{exp} (e) w/o L_{col} (f) w/o $L_{tv_{\mathcal{A}}}$

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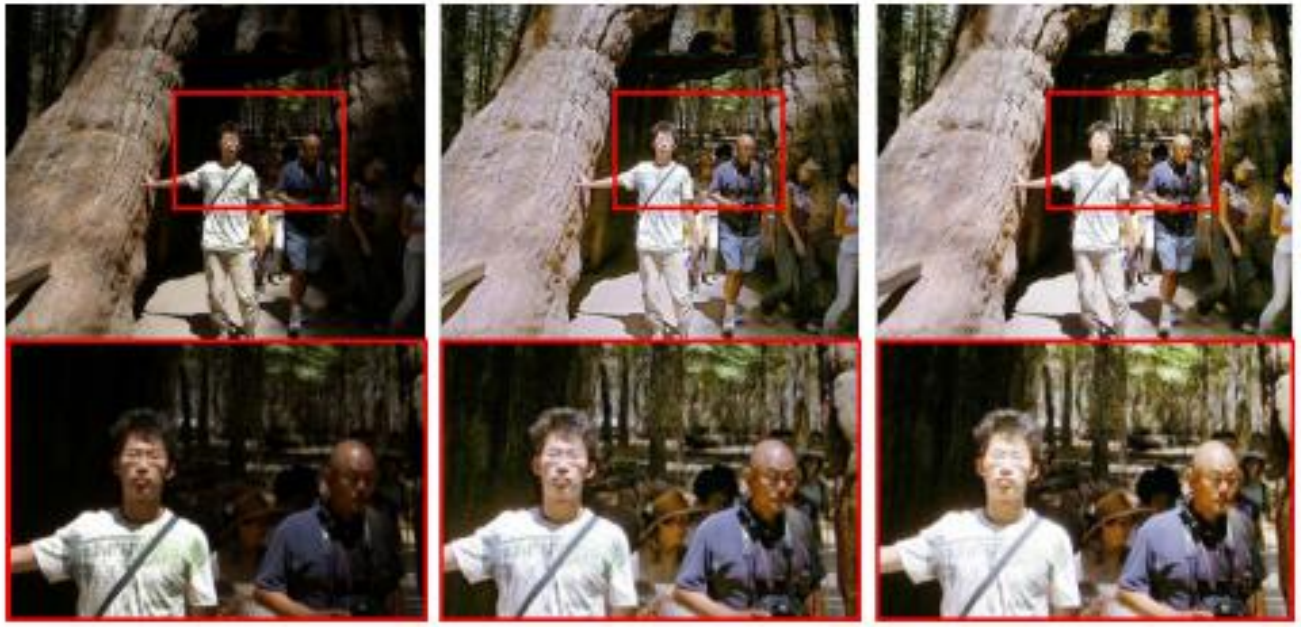
Part 3: Zero-DCE++

Zero-DCE++

- Redesign Network Structure
- Reformulate Curve Formation
- Control Sizes of Input Image



(a) input (b) Zero-DCE (c) Zero-DCE++

Redesigned Network

- Convolutional Layers --> Depthwise Separable Convolution Layers

Reformulated Curve Formation

$$LE_n(\mathbf{x}) = LE_{n-1}(\mathbf{x}) + \mathcal{A}_n(\mathbf{x}) LE_{n-1}(\mathbf{x})(1 - LE_{n-1}(\mathbf{x}))$$

$$LE_n(\mathbf{x}) = LE_{n-1}(\mathbf{x}) + \mathcal{A}(\mathbf{x}) LE_{n-1}(\mathbf{x})(1 - LE_{n-1}(\mathbf{x}))$$

(a) input (b) iteration 1 (c) iteration 2 (d) iteration 8 (e) difference1_2 (f) difference1_8

Control Sizes of Input Image

(a) input (b) original resolution (c) 2×↓ (d) 12×↓ (e) 100×↓ (f) 300×↓

Metrics	original resolution	2×↓	4×↓	6×↓	12×↓	20×↓	50×↓	75×↓	100×↓	300×↓
PSNR	16.09	16.17	16.29	16.37	16.42	16.33	15.85	15.56	15.35	14.53
FLOPs	11.442	2.887	0.749	0.352	0.115	0.064	0.040	0.037	0.036	0.035

Zero-DCE VS. Zero-DCE++

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Zero-DCE

- **Trainable Parameters**: 79K
- **FLOPs**: 84.99 G (1200×900×3)
- **Runtime**: 500 FPS (1200×900×3)
- **Training Time**: 30 minutes

Zero-DCE++

- **Trainable Parameters**: 10K
- **FLOPs**: 0.115 G (1200×900×3)
- **Runtime**: 1000 FPS (1200×900×3)
- **Training Time**: 20 minutes

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Part 4: Experiments

Low-Light Scene **Zero-DCE**

first 100 frames for training

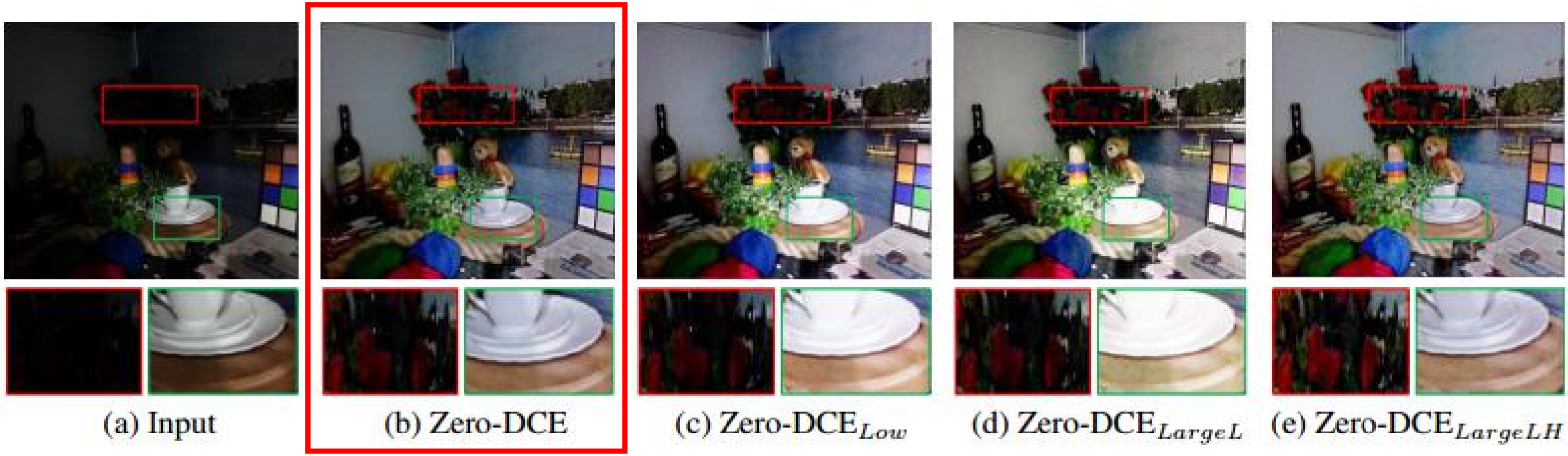
Low-Light Scene

Zero-DCE

Advantage of Three-Channel Adjustment

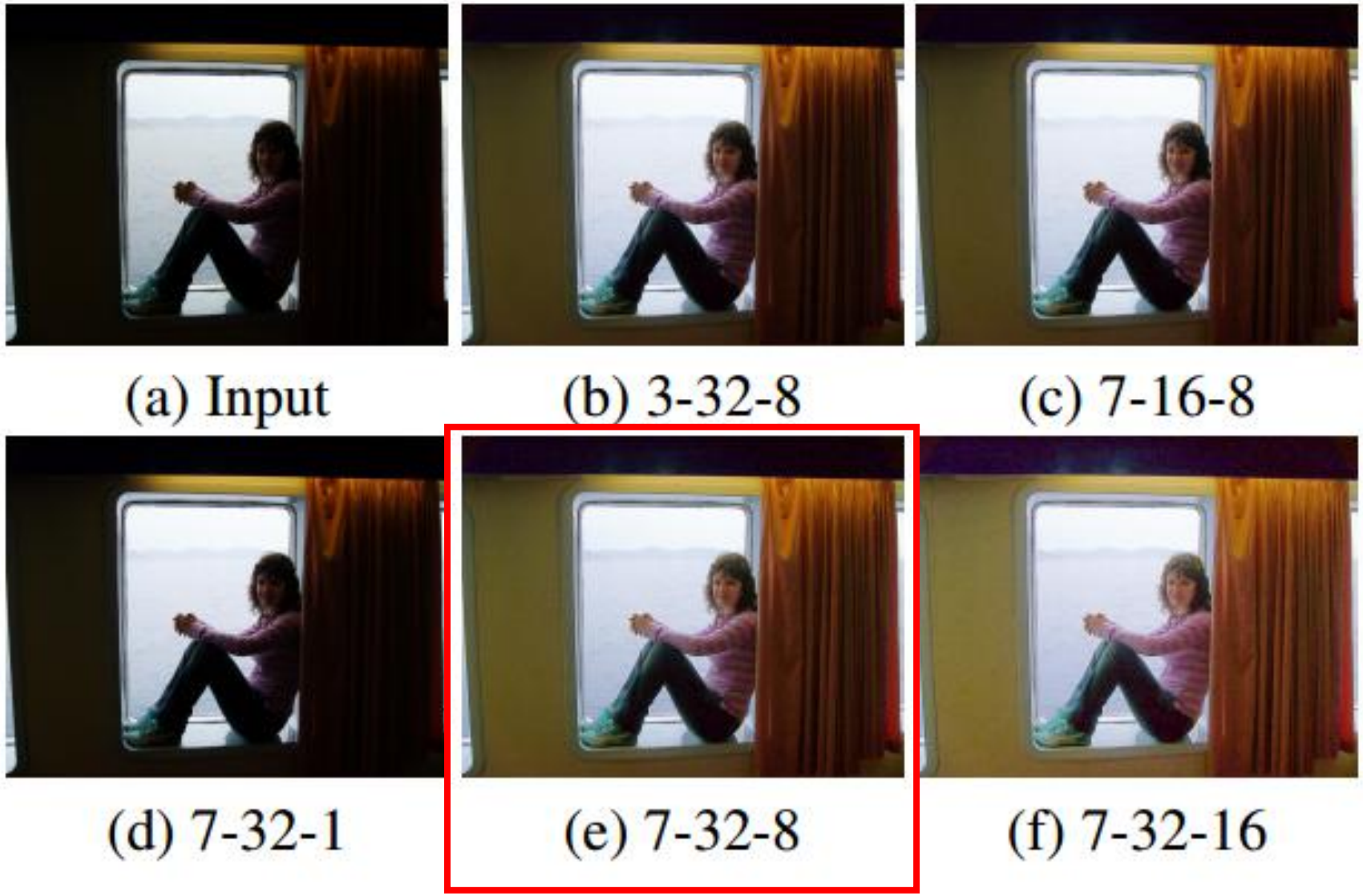
(a) Input (b) RGB (c) CIE Lab (d) YCbCr

Impact of Training Data



(a) Input (b) Zero-DCE (c) Zero-DCE$_{Low}$ (d) Zero-DCE$_{LargeL}$ (e) Zero-DCE$_{LargeLH}$

Effect of Parameter Settings

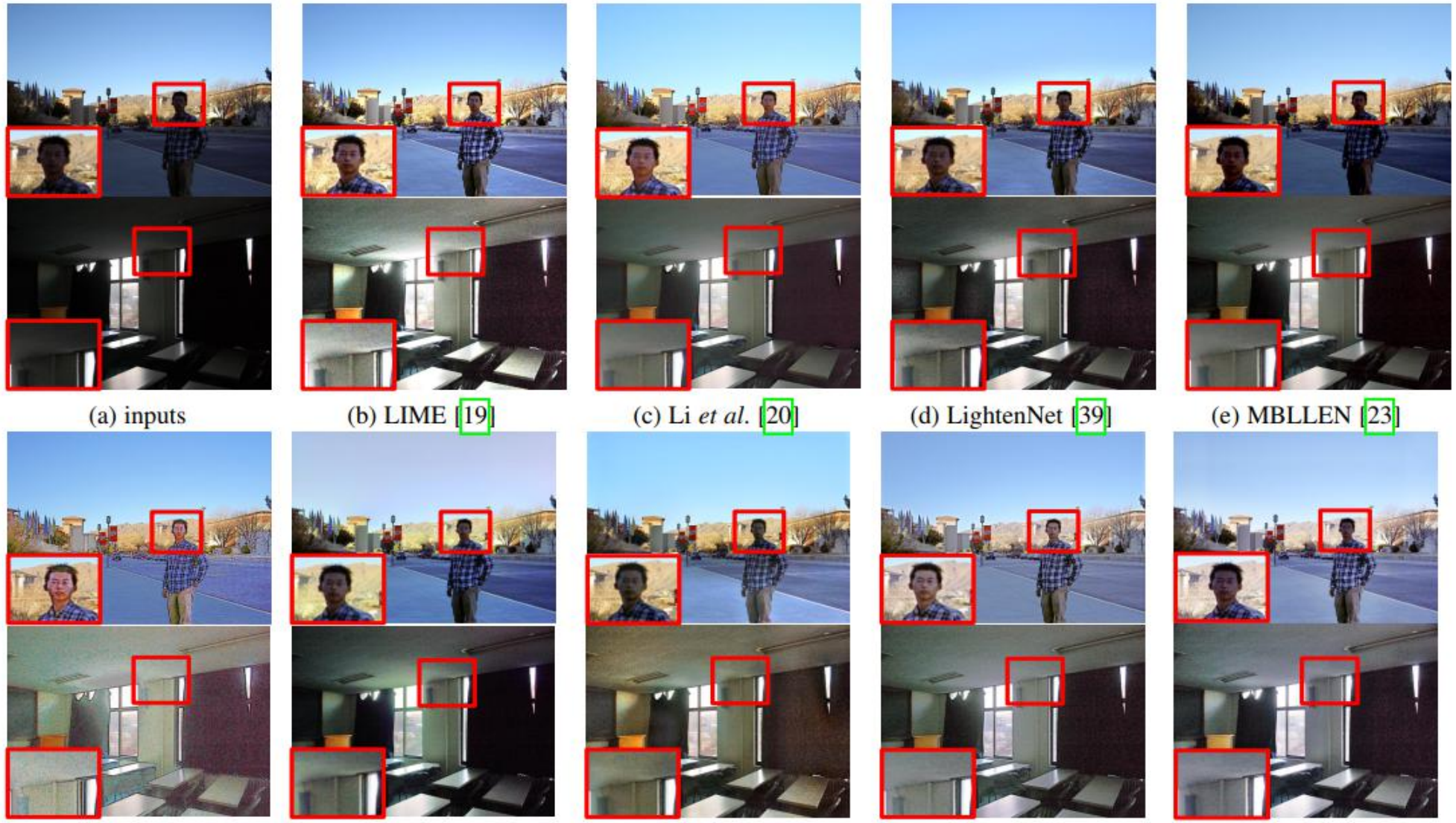


Effect of Well-Exposedness Level

(a) input (b) Zero-DCE$_{E0.4}$ (c) Zero-DCE$_{E0.5}$ (d) Zero-DCE$_{E0.6}$ (e) Zero-DCE$_{E0.7}$

$$L_{exp} = \frac{1}{M} \sum_{k=1}^{M} |Y_k - E|$$

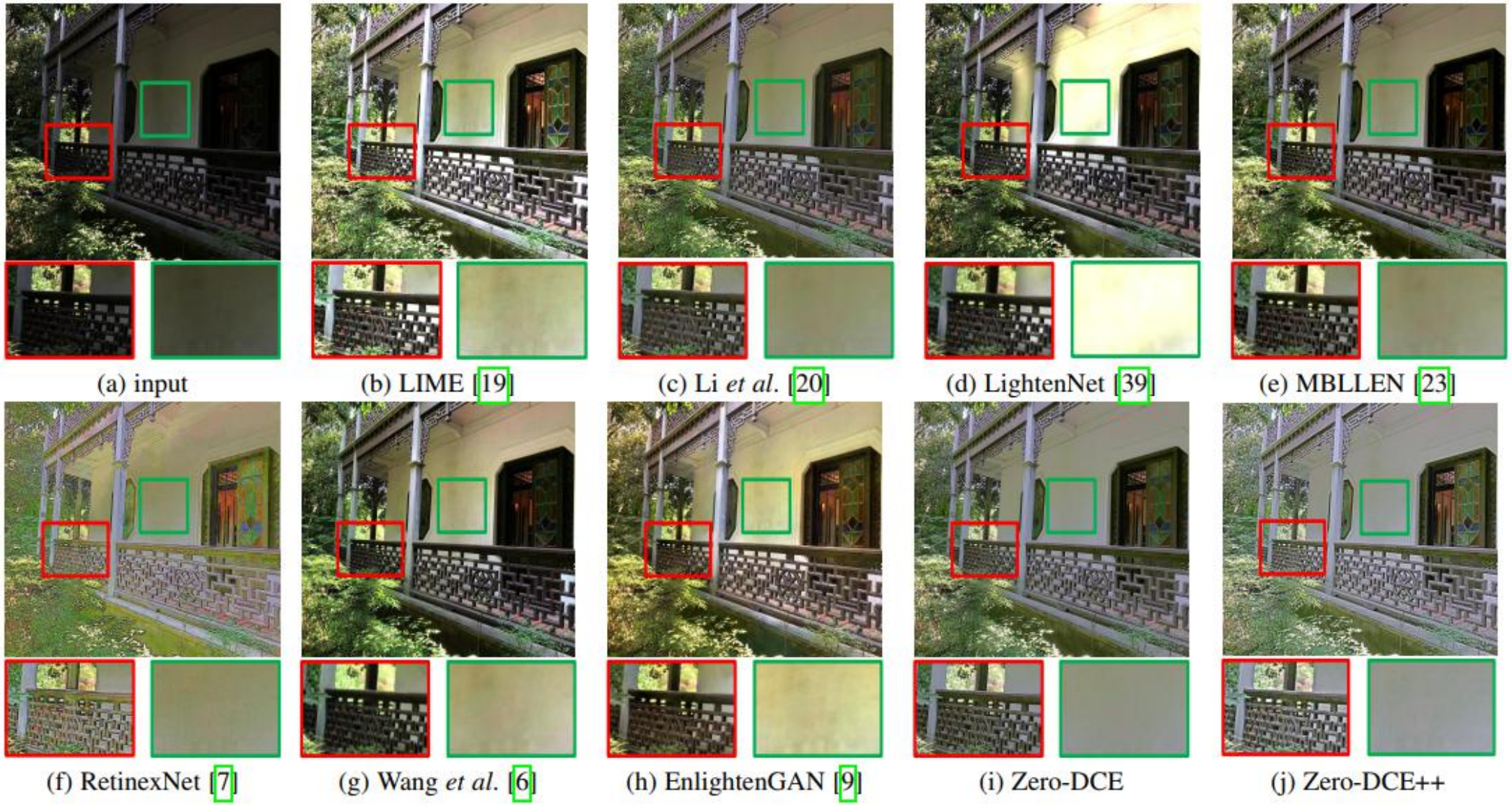
Comparisons



(a) inputs (b) LIME [19] (c) Li *et al.* [20] (d) LightenNet [39] (e) MBLLEN [23]

(f) RetinexNet [7] (g) Wang *et al.* [6] (h) EnlightenGAN [9] (i) Zero-DCE (j) Zero-DCE++

Comparisons



(a) input (b) LIME [19] (c) Li *et al.* [20] (d) LightenNet [39] (e) MBLLEN [23]

(f) RetinexNet [7] (g) Wang *et al.* [6] (h) EnlightenGAN [9] (i) Zero-DCE (j) Zero-DCE++

Comparisons

TABLE 5: User study (US)↑/Perceptual index (PI)↓ scores on the image sets (NPE, LIME, MEF, DICM, VV). Higher US score indicates better human subjective visual quality while lower PI value indicates better perceptual quality. The best result is in red whereas the second best one is in blue under each case.

Method	NPE	LIME	MEF	DICM	VV	Average
SRIE [18]	3.65/2.79	3.50/2.76	3.22/2.61	3.42/3.17	2.80/3.37	3.32/2.94
LIME [19]	3.78/3.05	3.95/3.00	3.71/2.78	3.31/3.35	3.21/3.03	3.59/3.04
Li *et al.* [20]	3.80/3.09	3.78/3.02	2.93/3.61	3.47/3.43	2.87/3.37	3.37/3.72
LightenNet [39]	3.76/2.88	3.02/2.84	3.07/2.51	3.11/3.13	2.55/3.29	2.70/2.93
MBLLEN [23]	3.81/2.77	3.77/3.18	3.21/3.04	3.07/3.19	2.72/3.63	3.33/3.16
RetinexNet [7]	3.30/3.18	2.32/3.08	2.80/2.86	2.88/3.24	1.96/2.95	2.58/3.06
Wang *et al.* [6]	3.83/2.83	3.82/2.90	3.13/2.72	3.44/3.20	2.95/3.42	3.43/3.01
EnlightenGAN [9]	3.90/2.96	3.84/2.83	3.75/2.45	3.50/3.13	3.17/4.71	3.63/3.22
Zero-DCE	3.81/2.84	3.80/2.76	4.13/2.43	3.52/3.04	3.24/3.33	3.70/2.88
Zero-DCE++	3.79/2.93	3.81/2.97	4.10/2.50	3.48/3.21	3.26/3.31	3.69/2.98

Comparisons

TABLE 6: Quantitative comparisons in terms of PSNR, SSIM, and MAE on the Part2 testing set. The best result is in red whereas the second best one is in blue under each case.

Method	PSNR↑	SSIM↑	MAE↓
SRIE [18]	14.41	0.54	127.08
LIME [19]	16.17	0.57	108.12
Li *et al.* [20]	15.19	0.54	114.21
RetinexNet [7]	15.99	0.53	104.81
LightenNet [39]	13.17	0.55	140.92
MBLLEN [23]	15.02	0.52	119.14
Wang *et al.* [6]	13.52	0.49	142.01
EnlightenGAN [9]	16.21	0.59	102.78
Zero-DCE	16.57	0.59	98.78
Zero-DCE++	16.42	0.58	102.87

Comparisons

TABLE 7: Runtime (RT, in second), trainable parameters (#P), and FLOPs (in G) comparisons. "-" indicates that the result is not available. The best result is in red whereas the second best one is in blue under each case.

Method	RT	#P	FLOPs	Platform
SRIE [18]	12.1865	-	-	MATLAB (CPU)
LIME [19]	0.4914	-	-	MATLAB (CPU)
Li *et al.* [20]	90.7859	-	-	MATLAB (CPU)
LightenNet [39]	25.7716	29,532	30.54	MATLAB (CPU)
MBLLEN [23]	13.9949	450,171	301.12	TensorFlow (GPU)
RetinexNet [7]	0.1200	555,205	587.47	TensorFlow (GPU)
Wang *et al.* [6]	0.0210	998,816	0.19	TensorFlow (GPU)
EnlightenGAN [9]	0.0078	8,636,675	273.24	PyTorch (GPU)
Zero-DCE	0.0025	79,416	84.99	PyTorch (GPU)
Zero-DCE++	0.0012	10,561	0.12	PyTorch (GPU)

Comparisons

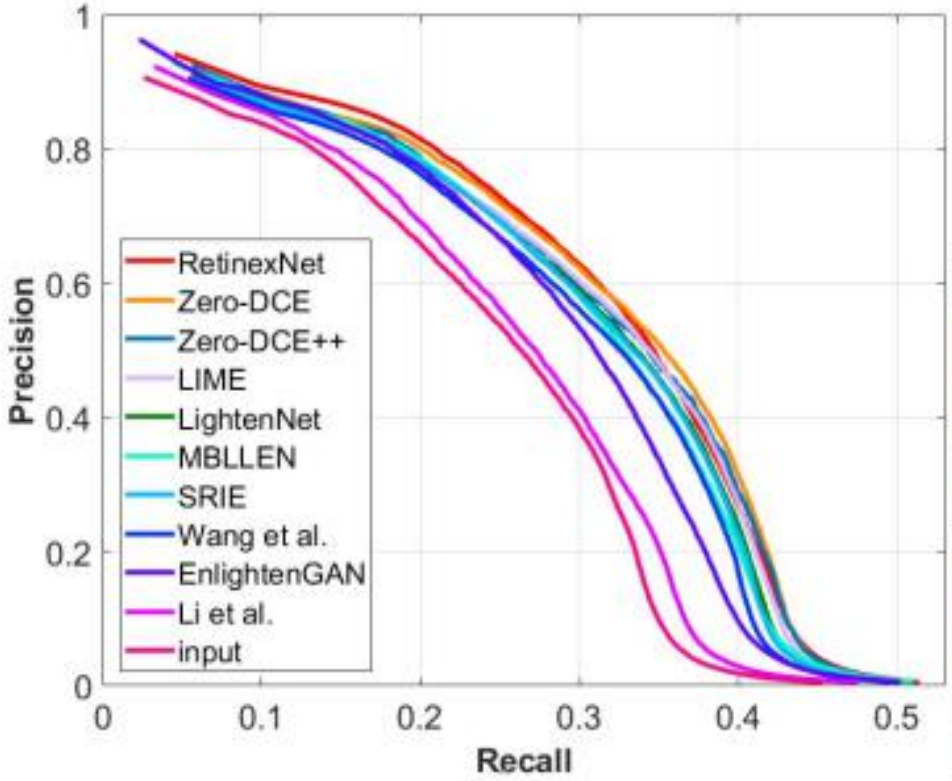


TABLE 8: The average precision (AP) for face detection in the dark under different IoU thresholds (0.5, 0.7, 0,9). The best result is in red whereas the second best one is in blue under each case.

Method	IoU thresholds		
	0.5	0.7	0.9
input	0.231278	0.007296	0.000002
SRIE [18]	0.288193	0.012621	0.000007
LIME [19]	0.293970	0.013417	0.000007
Li *et al.* [20]	0.243714	0.008616	0.000003
LightenNet [39]	0.290128	0.012581	0.000005
MBLLEN [23]	0.289232	0.013696	0.000007
RetinexNet [7]	0.304933	0.017545	0.000005
Wang *et al.* [6]	0.280068	0.011107	0.000003
EnlightenGAN [9]	0.276574	0.013204	0.000009
Zero-DCE	0.303135	0.014772	0.000005
Zero-DCE++	0.297977	0.014587	0.000005

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Part 5: Related Work

Related Work

Flexible Piecewise Curves Estimation for Photo Enhancement

https://arxiv.org/pdf/2010.13412.pdf

(a) FlexiCurve -trained with **paired** data

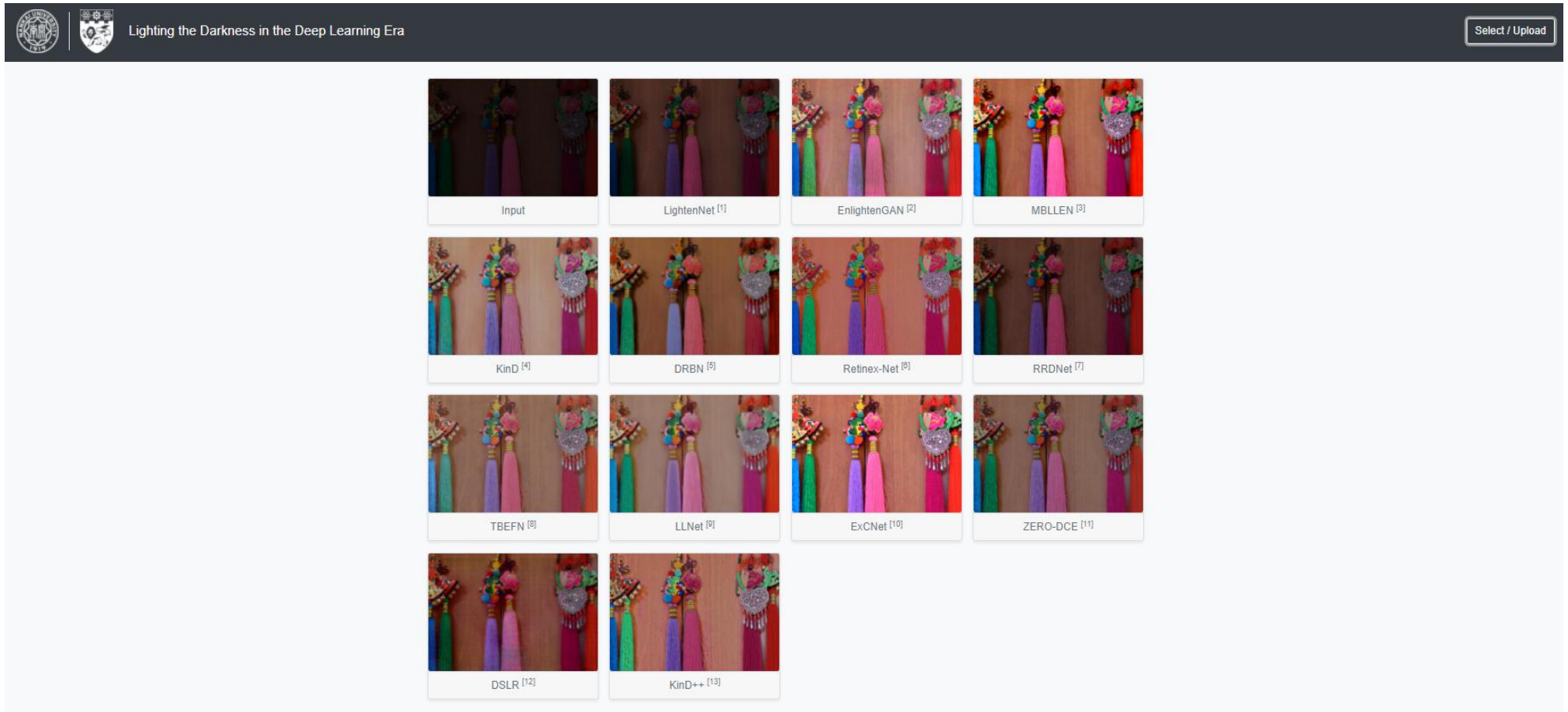
(b) FlexiCurve -trained with **unpaired** data

Related Work

Lighting the Darkness in the Deep Learning Era (NTU&Nankai&SenseTime)

Project Page: https://github.com/Li-Chongyi/Lighting-the-Darkness-in-the-Deep-Learning-Era-Open/

LoLi-Platform: http://mc.nankai.edu.cn/ll/



Thank you!