CV Final Project

Group 25

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Image Enhancement

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Introduce problem

2 **Method**
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3 **Results**
Qualitative and Quantitative Result

4 **Discussion**
The effect of modification

Motivation

Goal

- Enhance low-light images automatically
- Prevent over enhancing a normal light image

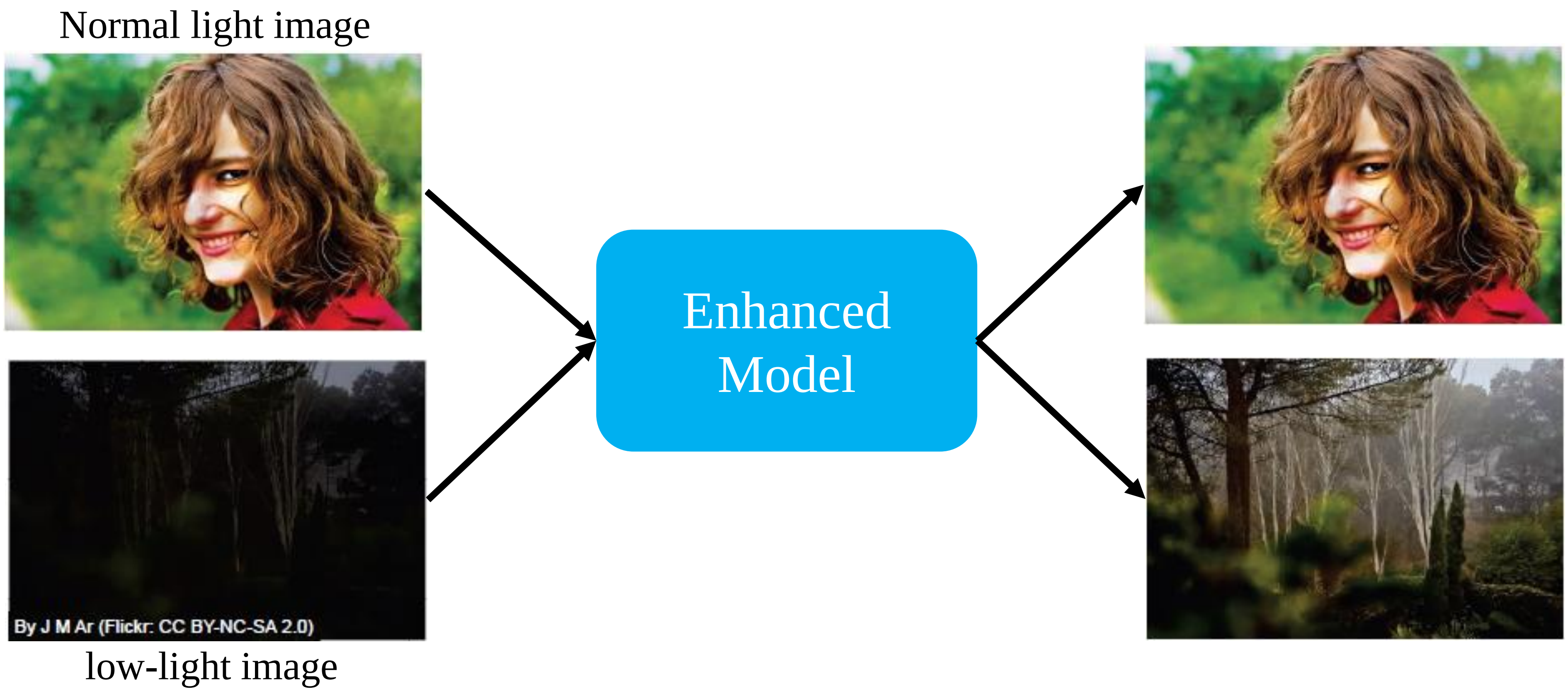


Fig. 1. An illustrate example for the image enhancement.

Motivation

Based on Zero-DCE [1]

Two problems

- The color will tend to become white

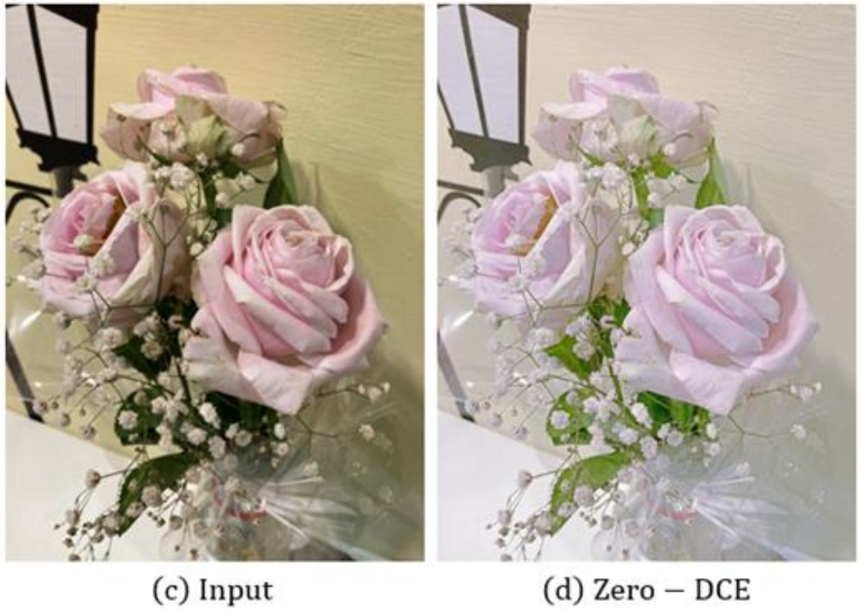


Fig. 2. The result that the color tend to be white

- Over enhancement

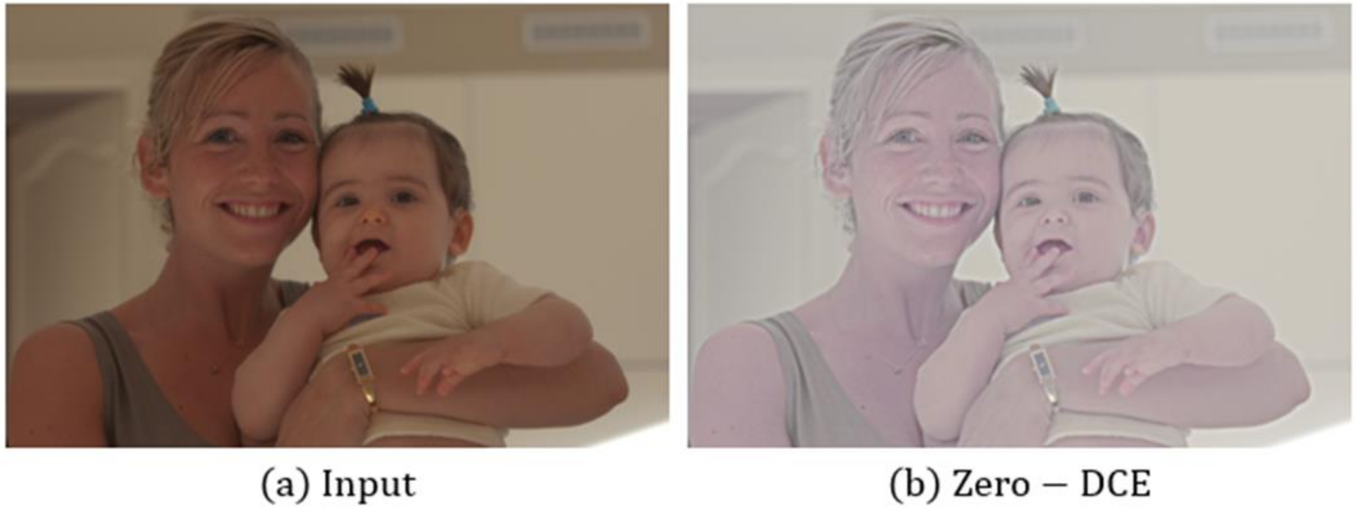


Fig. 3. Result that is over enhancement.

Purpose

- Our Work: modified the paper Zero-DCE
- To avoid the color of the image becomes white and over enhancement

[1] C. Guo et al. Zero − reference deep curve estimation for low − light image enhancement. In CVPR, 2020.

Method

1. Zero-DCE

- Formulate light enhancement as a task of image-specific curve estimation
- A lightweight deep network, DCE-Net

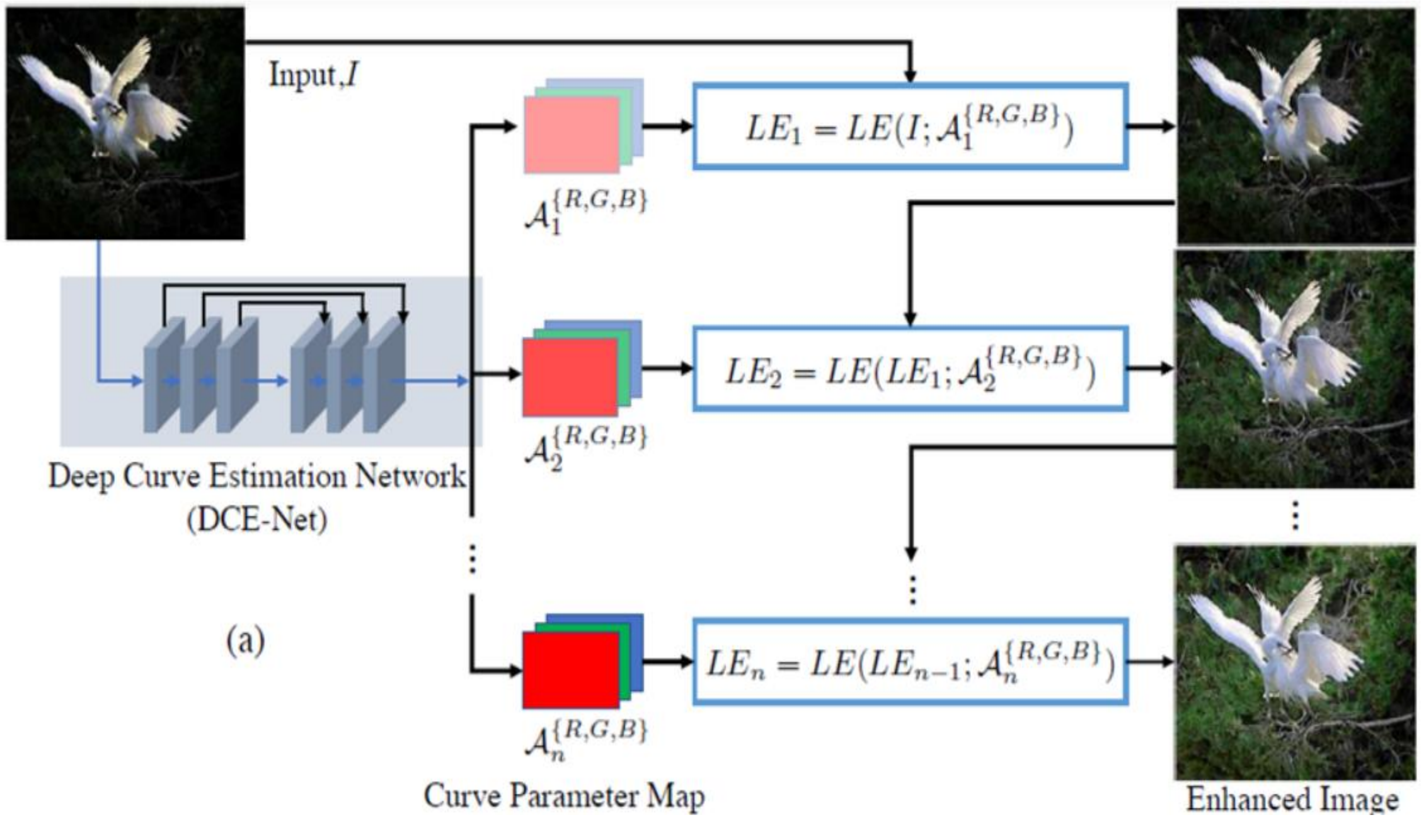
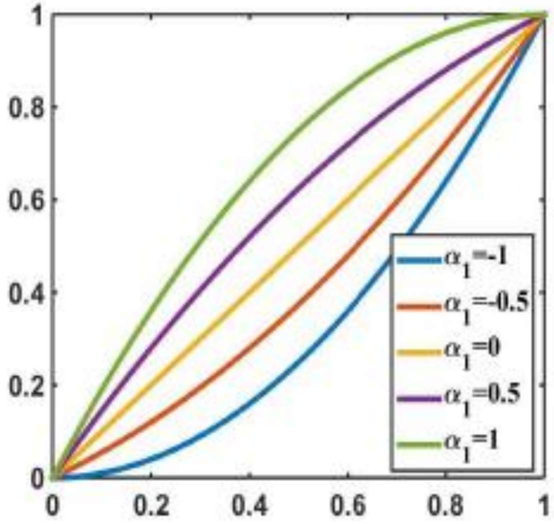


Fig. 4. The Zero-DCE architecture.

- Use a Quadratic function (degree=2)：

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

- Learned the curve parameter $\alpha \in [-1, 1]$



$$e.g.\ If\ \alpha = 1, then\ f(x) = -x^2 + 2x$$

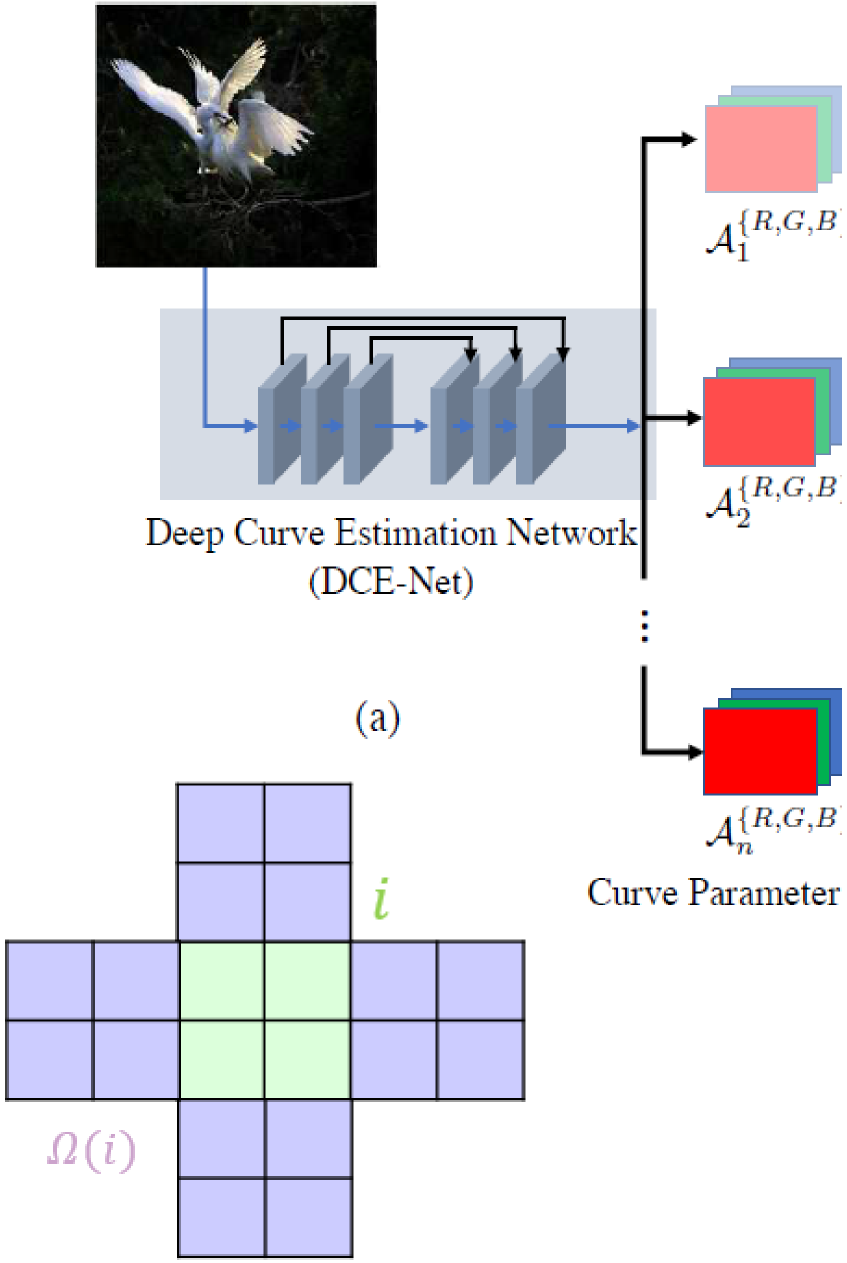
Proposed Method

DCE-Net

- Input：a low light image
- Output：8 parameter maps

Spatial Consistency Loss

- *Preserving the difference of neighboring regions between the input image and its enhanced version*
- Y, I：Average intensity value of local region in the enhanced version and input image, respectively
- $\mathcal{L}_{spa} = \frac{1}{K}\sum_{i=1}^{K}\sum_{j\in\Omega(i)}(|Y_i - Y_j| - |I_i - I_j|)$



Proposed Method

Exposure Control Loss

- Restrain under-/over-exposed regions
- Y ： Average intensity value of local region in the enhanced image
- E ： well-exposedness level
- $\mathcal{L}_{exp} = \frac{1}{M}\sum_{k=1}^{M}|Y_k - E|$

Color Constancy Loss

- Gray-World color constancy hypothesis ：color in each sensor channel averages to gray over the entire image.
- Correct the potential color deviations in the enhanced image
- $\mathcal{L}_{col} = \sum_{\forall(p,q)\in\varepsilon}|J^p - J^p|\,, \varepsilon = \{(R,G),(R,B),(G,B)\}$

Proposed Method

Illumination Smoothness Loss

- Preserve the monotonicity relations between neighboring pixels
- Y ：Average intensity value of local region in the enhanced image
- E ：Well-exposedness level
- $\mathcal{L}_{tv_{\mathcal{A}}} = \frac{1}{N}\sum_{n=1}^{N}\sum_{c\in\xi}\left(|\nabla_x \mathcal{A}_n^c| + |\nabla_y \mathcal{A}_n^c|\right), \xi \in \{R, G, B\}$

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

Method

2. Modification

- **Iterative:**
  - output only 3 parameter maps
  - the output of the previous iteration is an input of the next iteration
- **Stop Mechanism:**
  - mean of an image, $\mu(\mathrm{I})$, should be less than or equal to 0.6

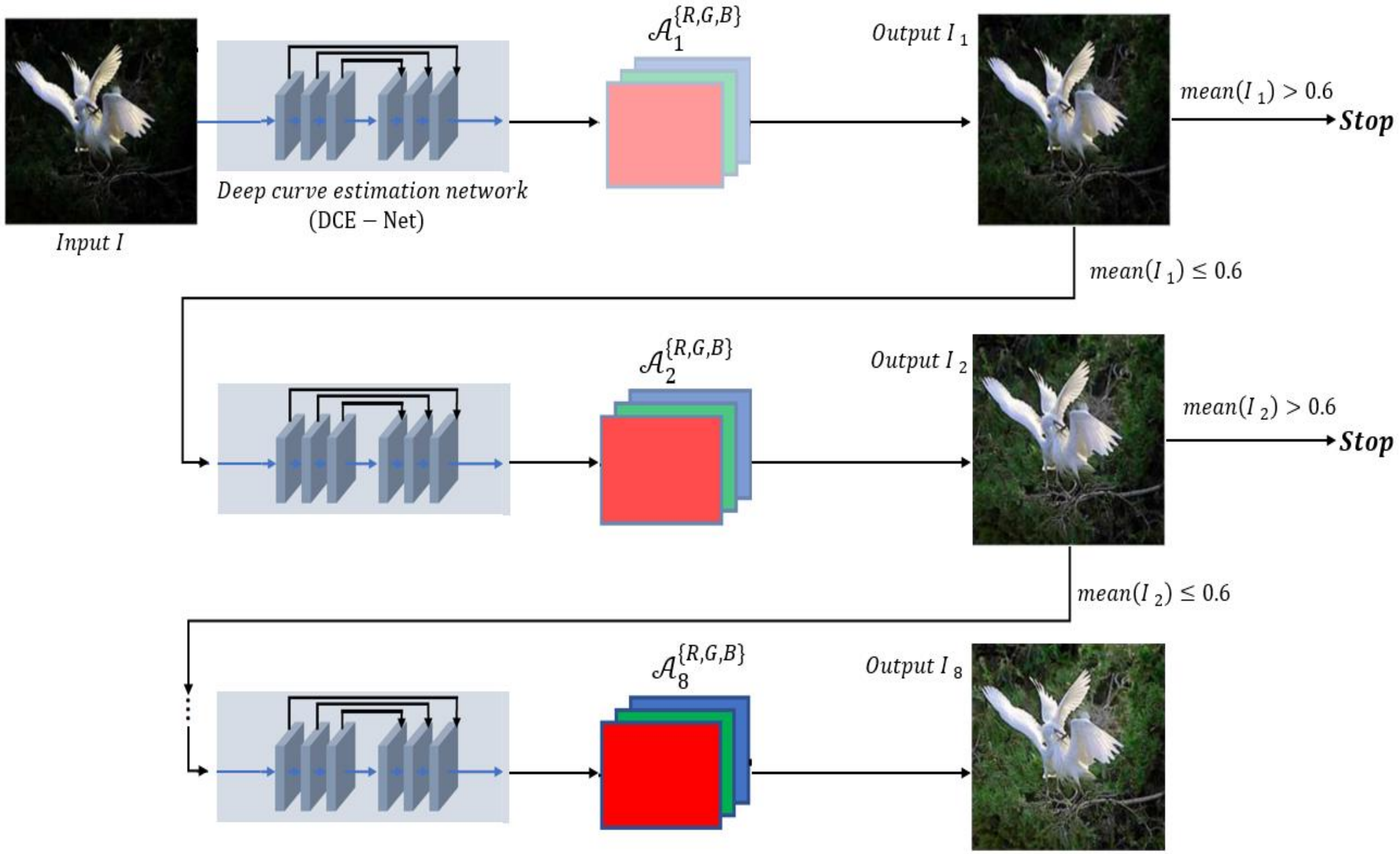


Fig. 4. The Zero-DCE++ architecture.

2. Modification

$$\text{Gray} = (\text{R}_{\text{avg}} + \text{R}_{\text{avg}} + \text{R}_{\text{avg}})/3$$

$$\text{R'} = \frac{\text{Gray}}{R_{avg}} R$$

$$\text{G'} = \frac{\text{Gray}}{G_{avg}} G$$

$$\text{B'} = \frac{\text{Gray}}{B_{avg}} B$$

- **Weighted Color Constancy Loss: (inspired by [2])**

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

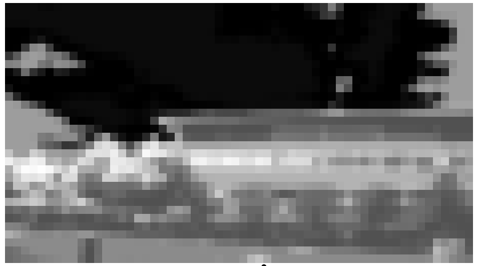
- S is the segmentation map,

- $\odot$ denotes the element-wise product.

input

Gray world

[2]



segmentation map

- **Color Consistency Loss:**
  - Transform the input image I (RGB color space) to enhanced image I' (YCbCr color space)
  - $L_{ccl} = \frac{1}{HW} \sum_{c \in \xi} (I^c - I'^c)^2 ,\ \xi = \{Cb, Cr\}$, where HW is the number of pixels.

[2] Chen Guanghua and Zhang Xiaolong. A Method to Improve Robustness of the GrayWorld Algorithm. In ICCMCEE, 2015.

Results

Datasets

- Our dataset: Lucy
- VV, MEF, LOL, LIME, FiveK, DICM

Evaluation metric

- NIMA

Results (normal)

- **Visual results**

1.a. Input

1.b. Zero-DCE

1.c. Iterative Zero-DCE++

1.d. Iterative Zero-DCE++ w/ stop

1.e. Weighted color constancy loss

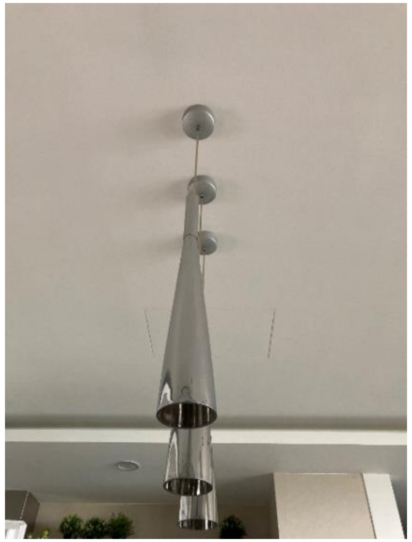
1.f. Weighted color constancy loss (stop)

1.g. Color consistency loss

1.h. Color consistency loss (stop)

Results (normal)

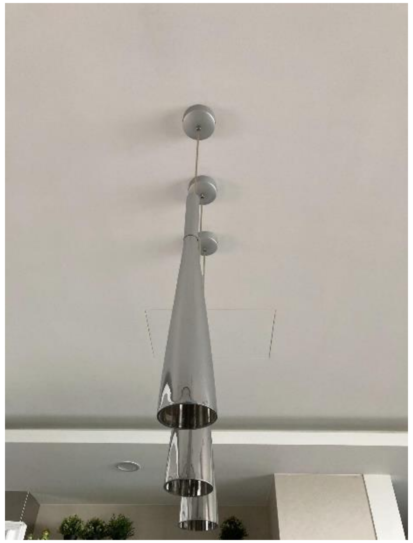
- **Visual results**



2.a. Input

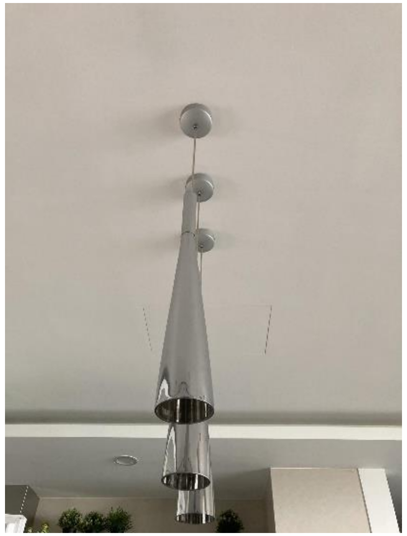
2.b. Zero-DCE

2.c. Iterative Zero-DCE++



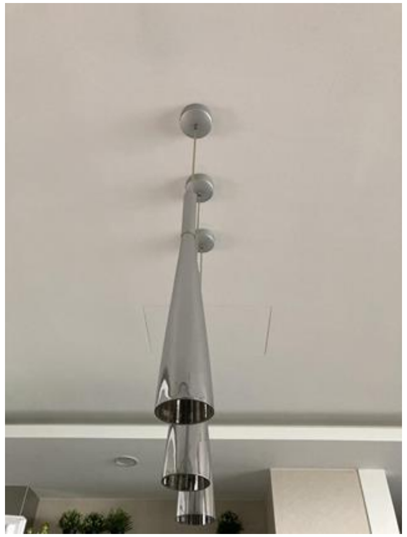
2.d. Iterative Zero-DCE++ w/ stop

2.e. Weighted color constancy loss



2.f. Weighted color constancy loss (stop)

2.g. Color consistency loss



2.h. Color consistency loss (stop)

Results (normal)

- **Visual results**

3.a. Input

3.b. Zero-DCE

3.c. Iterative Zero-DCE++

3.d. Iterative Zero-DCE++ w/ stop

3.e. Weighted color constancy loss

3.f. Color consistency loss

Results (low light)

- **Visual results**

4.a. Input

4.b. Zero-DCE

4.c. Iterative Zero-DCE++

4.d. Iterative Zero-DCE++ w/ stop

4.e. Weighted color constancy loss

4.f. Color consistency loss

Results (low light)

- **Visual results**

5.a. Input

5.b. Zero-DCE

5.c. Iterative Zero-DCE++

5.d. Iterative Zero-DCE++ w/ stop

5.e. Weighted color constancy loss

5.f. Color consistency loss

Results (low light)

- **Visual results**

6.a. Input

6.b. Zero-DCE

6.c. Iterative Zero-DCE++

6.d. Iterative Zero-DCE++ w/ stop

6.e. Weighted color constancy loss

6.f. Color consistency loss

Results (low light)

- **Visual results**

7.a. Input

7.b. Zero-DCE

7.c. Iterative Zero-DCE++

7.d. Iterative Zero-DCE++ w/ stop

7.e. Weighted color constancy loss

7.f. Color consistency loss

Results (low light)

- **Visual results**

8.a. Input

8.b. Zero-DCE

8.c. Iterative Zero-DCE++

8.d. Iterative Zero-DCE++ w/ stop

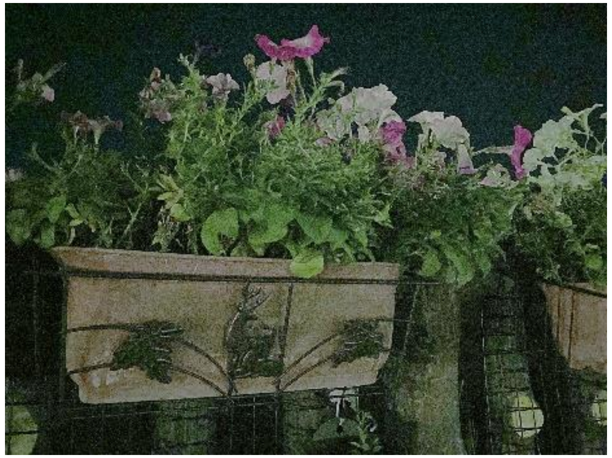
8.e. Weighted color constancy loss

8.f. Color consistency loss

Results (extremely dark)

- **Visual results**

9.a. Input



9.b. Zero-DCE

9.c. Iterative Zero-DCE++

9.d. Iterative Zero-DCE++ w/ stop

9.e. Weighted color constancy loss

9.f. Color consistency loss

Results (extremely dark)

- **Visual results**

10.a. Input

10.b. Zero-DCE

10.c. Iterative Zero-DCE++

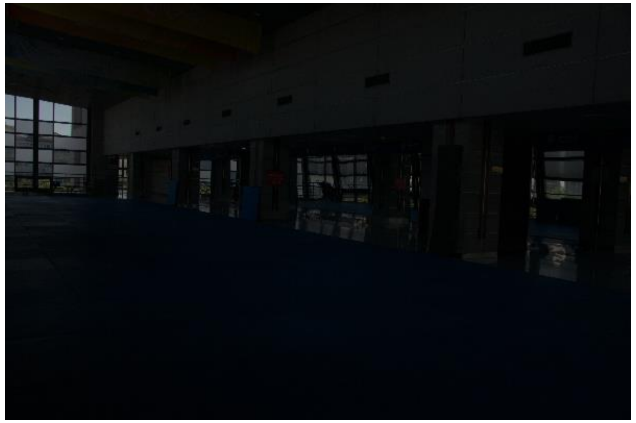
10.d. Iterative Zero-DCE++ w/ stop

10.e. Weighted color constancy loss

10.f. Color consistency loss

Results (extremely dark)

- **Visual results**



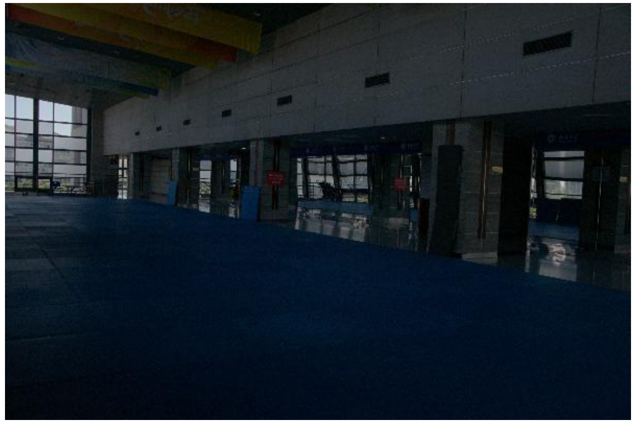
11.a. Input

11.b. Zero-DCE

11.c. Iterative Zero-DCE++

11.d. Iterative Zero-DCE++
w/ stop

11.e. Weighted color
constancy loss



11.f. Color consistency
loss

Results

- **Quantitative results**

	Lucy	VV	MEF	LOL	LIME	FiveK	DICM
Zero-DCE	4.725	**4.579**	4.618	**4.755**	4.549	4.141	4.382
Iterative Zero-DCE++	4.747	4.564	4.433	3.962	4.635	4.242	**4.485**
Iterative Zero-DCE++ w/ stop	4.741	4.564	4.333	3.962	4.634	4.239	4.481
Iterative Zero-DCE++ w/ weighted color constancy loss	**4.762**	4.544	**4.644**	4.251	**4.725**	**4.389**	4.477
Iterative Zero-DCE++ w/ color consistency loss	**4.762**	4.544	**4.644**	4.251	**4.725**	**4.389**	4.477

NIMA↑

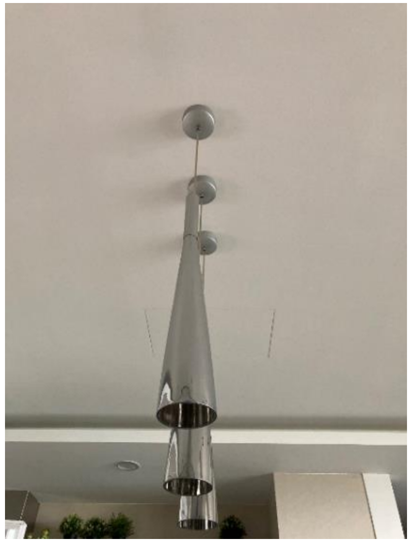
Discussion

Normal-light images.

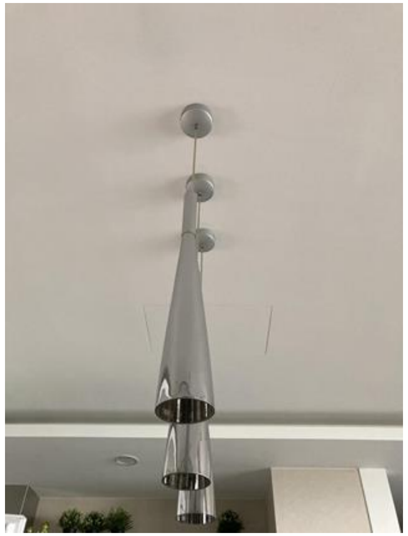
- Hope that our model will not enhance a normal image too much.
- Observing Fig 1.f, 2.f:
  - **color consistency loss:** only enhance its brightness and remain the color.
  - **Stop mechanism:** avoids color deviation.

1.a. Input

1.f. Color consistency loss



2.a. Input



2.f. Color consistency loss

Work plan

Low-Light images.

- The brightness should be increased and the color should be remained.
- Observing Fig 4 ~8: Zero-DCE enhance the brightness significantly.
- With color consistency loss: closer to the color its of corresponding input image.

4.a. Input

4.b. Zero-DCE

4.f. Color consistency loss

color may change a little bit

closer to the color its of corresponding input image

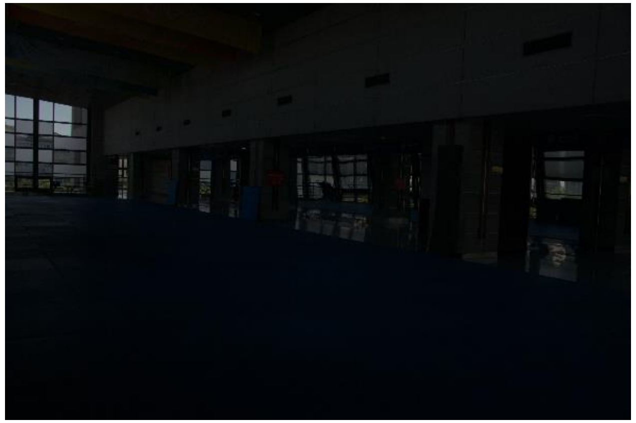
Discussion

Extreme Dark images.

- Increasing the brightness is the most important part.
- Color consistency is less important.
- Fig. 9~11: Zero-DCE can enhance the brightness of image much more than the other methods.

9.a. Input

9.b. Zero-DCE



11.a. Input

11.b. Zero-DCE

Noise is amplified.

Work assignment plan between team

- We finish and discuss all the works together.
- Each member focus on different part：

  郭家瑋：Code, 江梓豪: Report, 范氏和兒: PPT file