RDGAN: RETINEX DECOMPOSITION BASED ADVERSARIAL LEARNING FOR LOW-LIGHT ENHANCEMENT

Supplementary File

1. DISCRIMINATOR NETWORK

In this section, we introduce the discriminator network which is not shown in the paper. As shown in Fig.1, our discriminator network consists of 6 convolutional layers and ends with a fully-connected layer. PReLU activation function is used as well. Standard batch normalization is replaced by instance normalization[1] to avoid each image being affected by the others in the same batch during the normalization procedure.

We use the $RDGAN\_d$ loss introduced in the paper to train the discriminator network, which can be formulated as follow, in which $\mathcal{D}_{fake}$ and $\mathcal{D}_{real}$ denotes the probability judged by the discriminator network that the input image belongs to enhanced images or reference images, and Out_R denotes the decomposed Reflectance of the enhanced result Out by RDNet:

$$\mathcal{L}_{RDGAN\_d} = -\frac{1}{N}\sum_{j=1}^{N}(\log \mathcal{D}_{real}(Label_R^j) + \log \mathcal{D}_{fake}(Out_R^j)) \tag{1}$$

2. ENHANCEMENT COMPARISON

In this section, we conduct more experiments. These testing images are not paired with reference high quality images, thus the computation of PSNR and FSIMc is not available. Benchmark methods include Retinex-based methods NPEA[2], SRIE[3], Fu[4], LIME[5], JIEP[6], CRM[7], RobustRetinex[8], and learning-based methods GLADNet[9], RetinexNet[10].

3. REFERENCES

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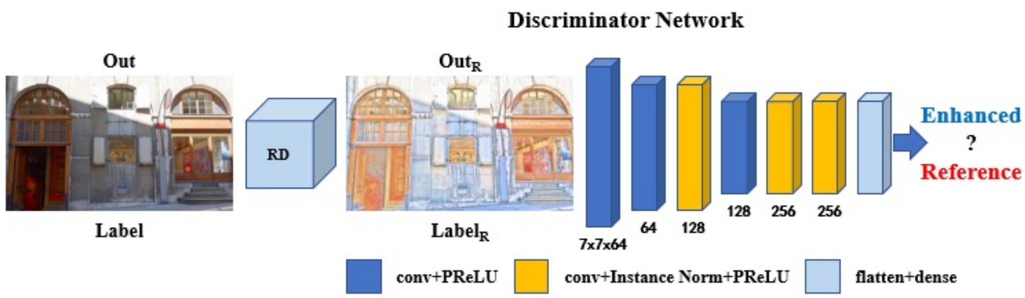


Fig. 1. The discriminator network architecture.

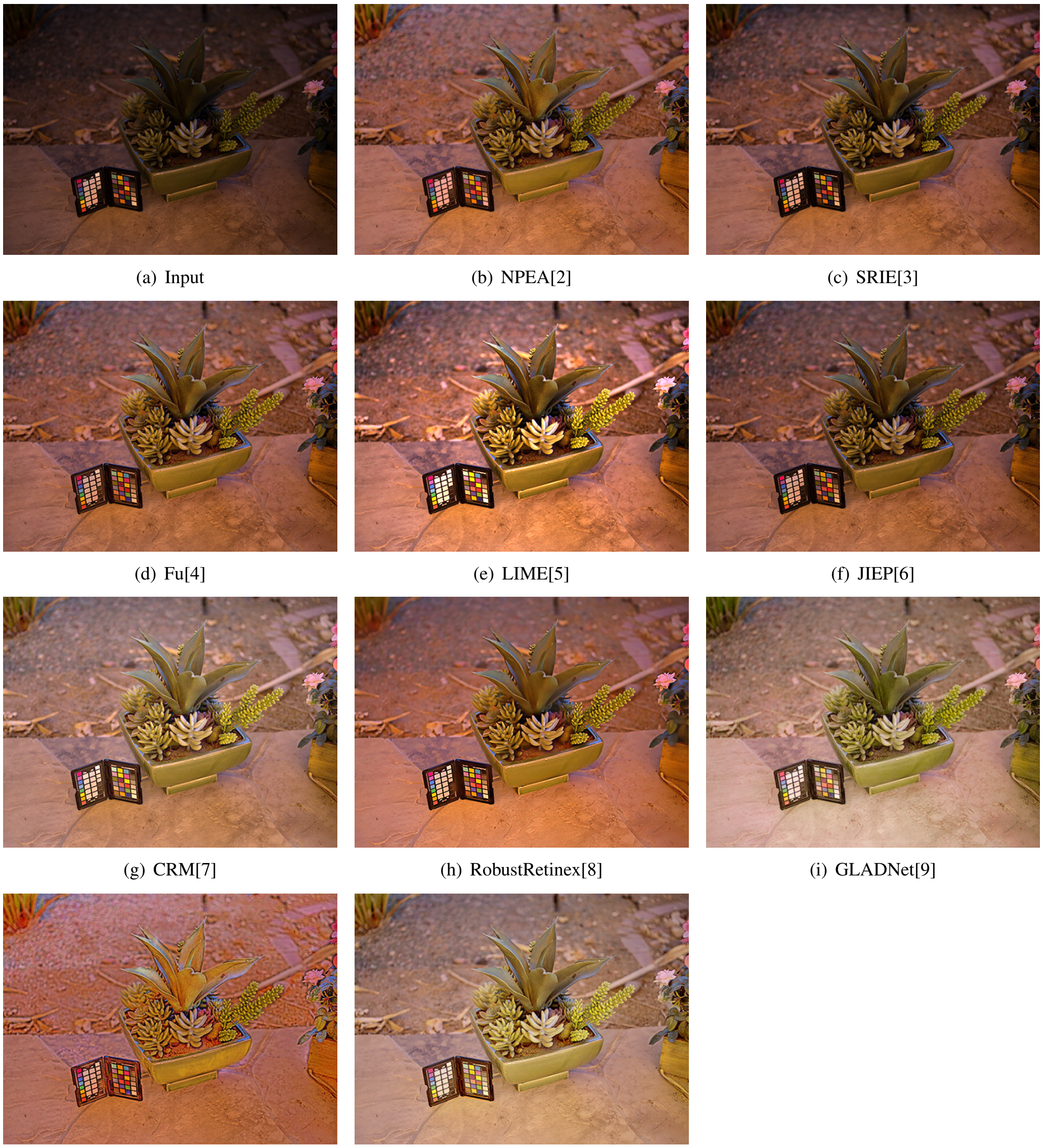
(a) Input (b) NPEA[2] (c) SRIE[3]

(d) Fu[4] (e) LIME[5] (f) JIEP[6]

(g) CRM[7] (h) RobustRetinex[8] (i) GLADNet[9]

(j) RetinexNet[10] (k) RDGAN

Fig. 2. The enhanced results of the low-light image *Moonlight* from LIME[5] dataset by different methods. (a) Input (b) NPEA[2] (c) SRIE[3] (d) Fu[4] (e) LIME[5] (f) JIEP[6] (g) CRM[7] (h) RobustRetinex[8] (i) GLADNet[9] (j) RetinexNet[10] (k) RDGAN



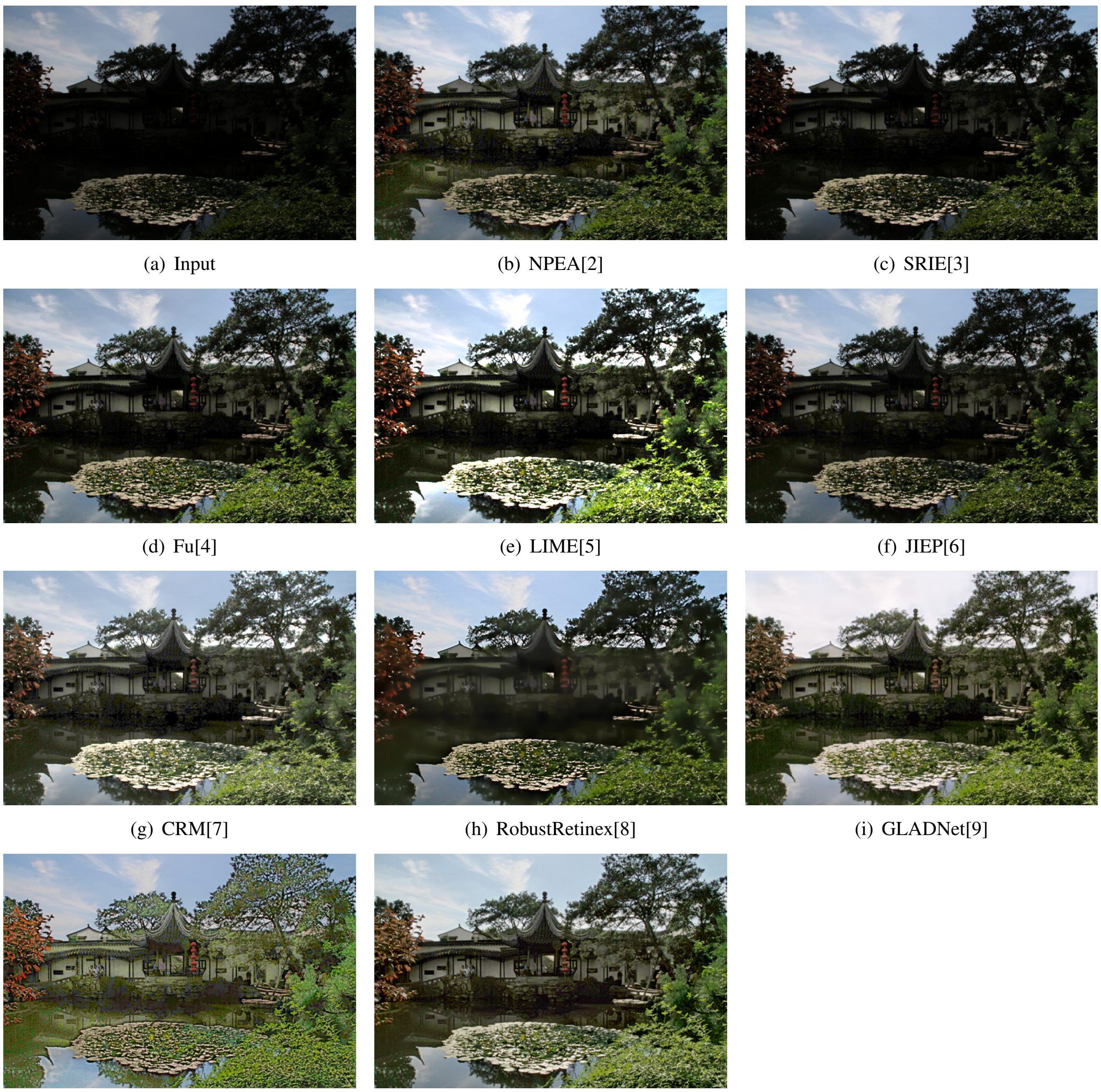
(a) Input (b) NPEA[2] (c) SRIE[3]

(d) Fu[4] (e) LIME[5] (f) JIEP[6]

(g) CRM[7] (h) RobustRetinex[8] (i) GLADNet[9]

(j) RetinexNet[10] (k) RDGAN

Fig. 3. The enhanced results of the low-light image *Plant* from LIME[5] dataset by different methods. (a) Input (b) NPEA[2] (c) SRIE[3] (d) Fu[4] (e) LIME[5] (f) JIEP[6] (g) CRM[7] (h) RobustRetinex[8] (i) GLADNet[9] (j) RetinexNet[10] (k) RDGAN



(a) Input (b) NPEA[2] (c) SRIE[3]

(d) Fu[4] (e) LIME[5] (f) JIEP[6]

(g) CRM[7] (h) RobustRetinex[8] (i) GLADNet[9]

(j) RetinexNet[10] (k) RDGAN

Fig. 4. The enhanced results of the low-light image *Chinese Garden* from MEF[11] dataset by different methods. (a) Input (b) NPEA[2] (c) SRIE[3] (d) Fu[4] (e) LIME[5] (f) JIEP[6] (g) CRM[7] (h) RobustRetinex[8] (i) GLADNet[9] (j) RetinexNet[10] (k) RDGAN

(a) Input (b) NPEA[2] (c) SRIE[3]
(d) Fu[4] (e) LIME[5] (f) JIEP[6]
(g) CRM[7] (h) RobustRetinex[8] (i) GLADNet[9]
(j) RetinexNet[10] (k) RDGAN

Fig. 5. The enhanced results of the low-light image *Candle* from MEF[11] dataset by different methods. (a) Input (b) NPEA[2] (c) SRIE[3] (d) Fu[4] (e) LIME[5] (f) JIEP[6] (g) CRM[7] (h) RobustRetinex[8] (i) GLADNet[9] (j) RetinexNet[10] (k) RDGAN

(a) Input (b) NPEA[2] (c) SRIE[3]
(d) Fu[4] (e) LIME[5] (f) JIEP[6]
(g) CRM[7] (h) RobustRetinex[8] (i) GLADNet[9]
(j) RetinexNet[10] (k) RDGAN

Fig. 6. The enhanced results of the low-light image *Kluki* from MEF[11] dataset by different methods. (a) Input (b) NPEA[2] (c) SRIE[3] (d) Fu[4] (e) LIME[5] (f) JIEP[6] (g) CRM[7] (h) RobustRetinex[8] (i) GLADNet[9] (j) RetinexNet[10] (k) RDGAN