RDGAN: Retinex Decomposition based Adversarial Learning for Low-Light Enhancement

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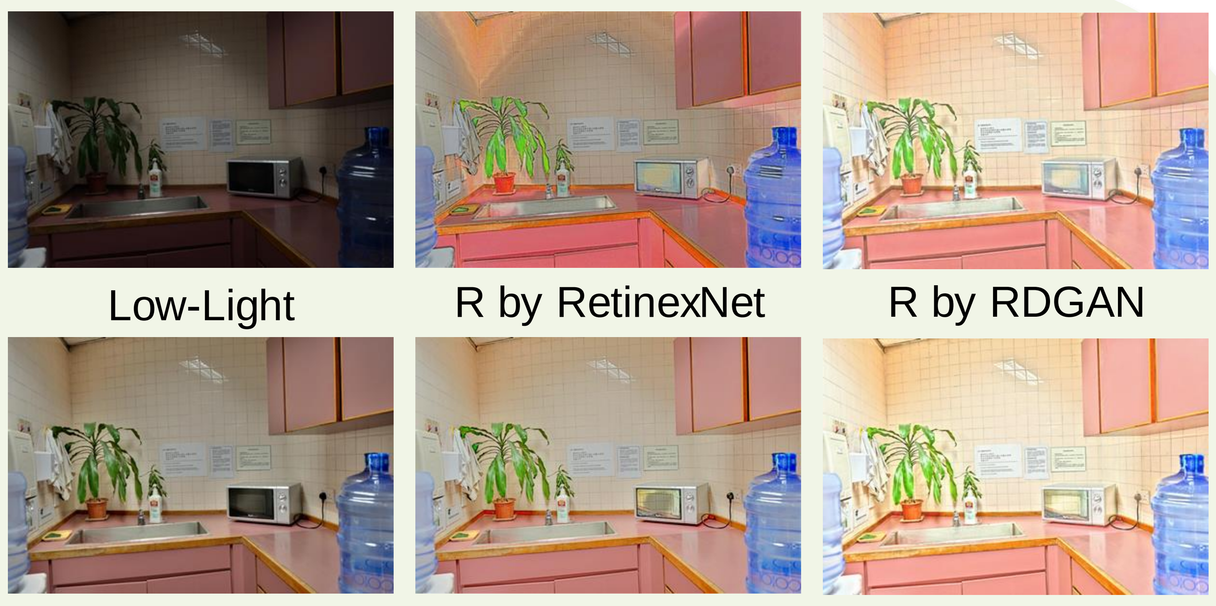
1. Low-Light Enhancement & Retinex Decomposition

Low-light image enhancement aims to improve the quality of photos taken under the low-light condition. Low-light images usually suffer from low contrast and loss of image details.

Retinex theory is a computational theory that decomposes an image **P** into two components, namely **I** (Illumination) and **R** (Reflectance), which can be formulated as **P = I ◦ R** . The **I** component is a grayscale image which is relatively smooth on the surface of the same object. The **R** component is a sRGB image which is relatively consistent under varying light conditions.
As shown in Fig. 1, where RetinexNet is a learning-based low-light enhancement approach, decomposed **R** components by our proposed RDGAN have fewer distortions.



Low-Light | R by RetinexNet | R by RDGAN
Well-Exposed | R by RetinexNet | R by RDGAN

Fig. 1 Comparison on Retinex decomposition.

2. Motivation & Contribution

Motivation:
For traditional Retinex-based methods, the decomposition results are optimized by iterations. Thus, when combining with other computer vision tasks, the overall framework is not end-to-end. For existing learning-based methods, the decomposition results lack of accuracy. Moreover, most Retinex-based methods only adjust the decomposed **I** component to obtain the final enhanced result, which neglects the distortions in the **R** component.

Contribution:

- We propose a framework with two networks: RDNet and FENet (see Fig. 2). Our RDNet learns to decompose the input image (no matter low-light or well-exposed) into **I** & **R** components (guided by its own **Bright Channel** after a morphological closing operation). A simple CRM function (Camera Response Model) is applied to the low-light image for a rough enhanced result (guide by its decomposed **I** component).
- Our FENet combines the enhanced result by CRM, the decomposed **R** component and the low-light image to generate the final enhanced result. We also design a novel adversarial loss, which is not computed on the enhanced results and the reference images but on their decomposed **R** components. Our new adversarial loss helps the generator network with color and detail restoration.

3. Our Proposed Framework

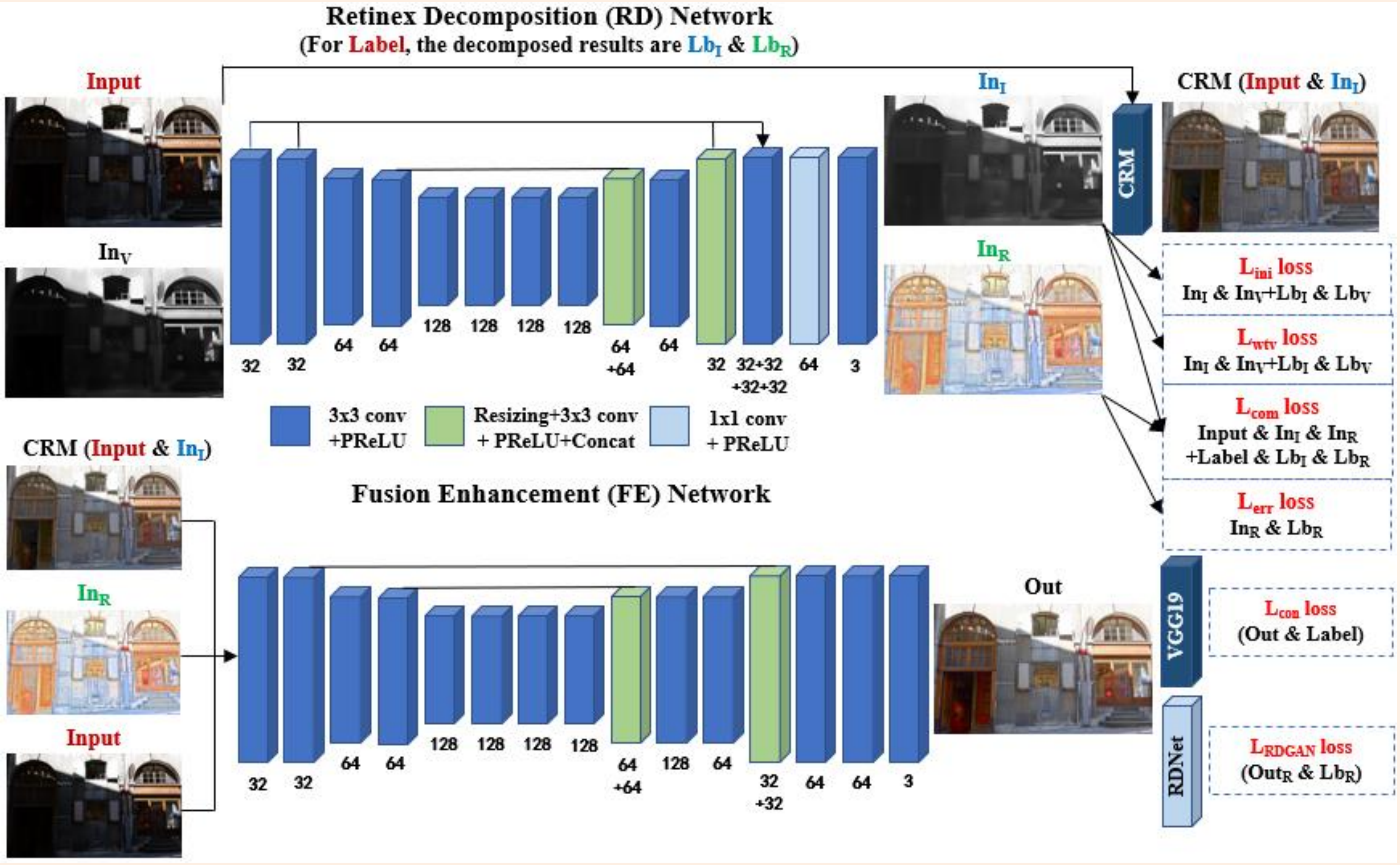


Fig. 2 Overview of our proposed RDGAN framework.

Loss Functions for RDNet

Initialization loss

$$\mathcal{L}_{ini} = \frac{1}{N}\sum_{j=1}^{N} ||In_I^j - In_V^j||^2 + ||Lb_I^j - Lb_V^j||^2$$

Weighted total variation loss

$$\mathcal{L}_{wtv} = \frac{1}{N}\sum_{j=1}^{N} \frac{||\nabla In_I^j||^2}{In_W^j|\nabla In_V^j| + \epsilon} + \frac{||\nabla Lb_I^j||^2}{Lb_W^j|\nabla Lb_V^j| + \epsilon}$$

Decomposition loss

$$\mathcal{L}_{com} = \frac{1}{N}\sum_{j=1}^{N} ||In_I^j \circ In_R^j - Input^j||^2 + ||Lb_I^j \circ Lb_R^j - Label^j||^2$$

Reflectance error loss

$$\mathcal{L}_{err} = \frac{1}{N}\sum_{j=1}^{N} ||In_R^j - Lb_R^j||^2$$

Loss Functions for FENet

Content perceptual loss

$$\mathcal{L}_{con} = \frac{1}{N}\sum_{j=1}^{N} ||V_{5\_4}(Out^j) - V_{5\_4}(Label^j)||^2$$

RDGAN adversarial loss

$$\mathcal{L}_{RDGAN\_d} = -\log \mathcal{D}_{real}(Lb_R^j) - \log \mathcal{D}_{fake}(Out_R^j)$$

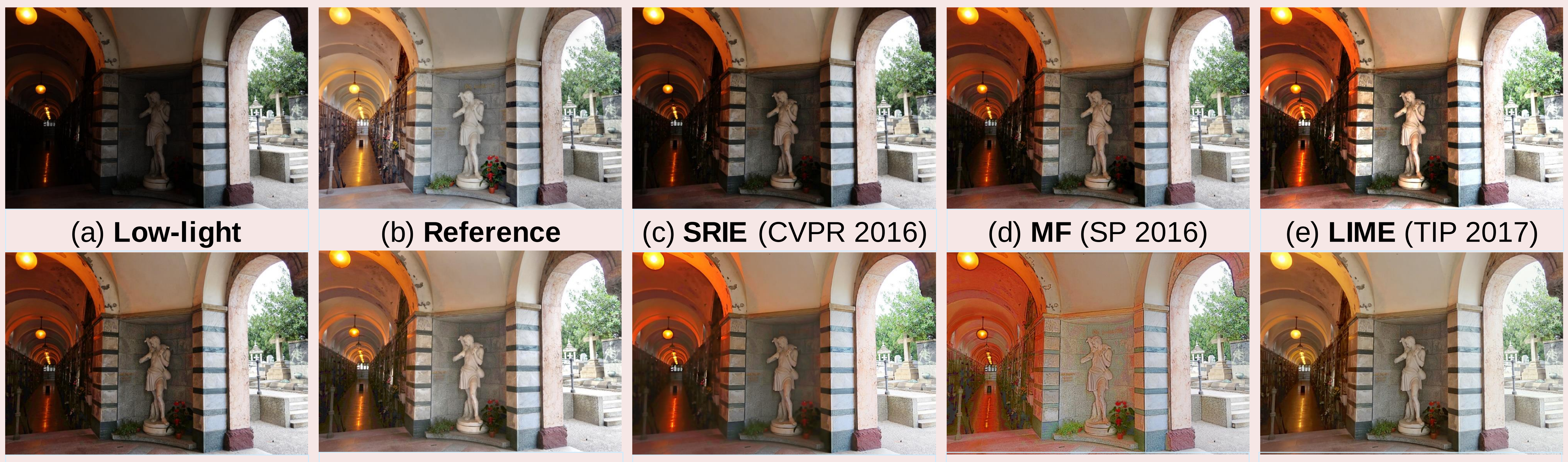
$$\mathcal{L}_{RDGAN\_g} = -\log \mathcal{D}_{real}(Out_R^j)$$

CRM Function

$$k = (\frac{1}{In_I + \epsilon})^a$$

$$CRM(In_I, Input) = e^{b(1-k)} Input^k$$

4. Experiment



(a) **Low-light** | (b) **Reference** | (c) **SRIE** (CVPR 2016) | (d) **MF** (SP 2016) | (e) **LIME** (TIP 2017)
(f) **JIEP** (ICCV 2017) | (g) **CRM** (ICCVW 2017) | (h) **RobustR** (TIP 2018) | (i) **RetinexNet** (BMVC 2018) | (j) **RDGAN**

Fig. 3 Visualization of state-of-the-art approaches on image ***Statue***.

Method	PSNR	FSIMc	Time(s)
NPEA [3]	19.81	0.9160	18.61
SRIE [4]	19.33	0.9221	18.35
MF [5]	21.17	0.9371	0.58
LIME [6]	19.93	0.8979	0.33
JIEP [7]	20.70	0.9375	9.48
CRM [8]	21.33	<u>0.9450</u>	0.51
RobustR [9]	**23.45**	0.9296	41.54
GLADNet [11]	21.65	0.9357	0.31(GPU)
RetinexNet [14]	18.67	0.8535	0.27(GPU)
RDGAN	<u>22.34</u>	**0.9583**	0.58(GPU)

Fig. 4 Comparison of state-of-the-art approaches on 53 testing images (1024x682).

Limitation:
Noises and JPEG artifacts that do not look obvious in the original low-light images may be amplified. One possible reason is that our approach, as well as existing low-light enhancement methods, cannot perfectly deal with the noises and JPEG artifacts in low-light images.