A JOINT MODEL-DRIVEN UNFOLDING NETWORK FOR DEGRADED LOW-QUALITY COLOR-DEPTH IMAGES ENHANCEMENT

Authors: Lijun Zhao*, Ke Wang*, Jinjing Zhang#, Jie Zhao* , Anhong Wang*

***Taiyuan University of Science and Technology, No.66 Waliu Road, Taiyuan 030024, China**
#North University of China, No.3 Xueyuan Road, Taiyuan 030051, China

OUTLINE

- 01 BACKGROUND
- 02 THE PROPOSED METHOD
- 03 EXPERIMENTAL RESULTS

01

BACKGROUND

01 BACKGROUND

- Under unfavorable low brightness environment, camera will ineluctably capture low-light color images, which greatly limits the visibility of human and machine, while the performance of Color-Guided Depth map Super-Resolution (CGD-SR) task is also affected by low-light color images.
- Most existing methods only consider low-light image enhancement problem or depth map super-resolution problem, which leads to two-stage processing. Obviously, these two problems can simultaneously solved to benefit each other.
- Besides, most of the CGD-SR methods only design deep black-box networks, which lack sufficient network interpretability.

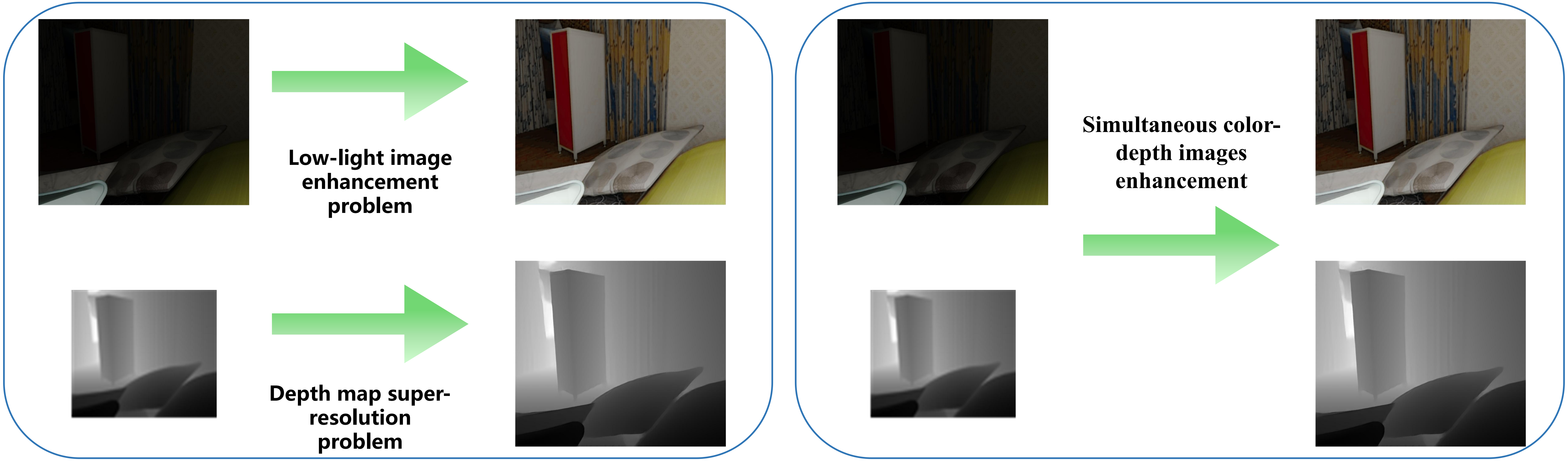

Fig. 1 The diagrams of the degraded low-quality color-depth images enhancement

02

THE PROPOSED METHOD

02 THE PROPOSED METHOD

- **Inspired by multi-task learning, degraded low-quality color-depth images enhancement tasks are transformed as a joint color-depth optimization model by using maximum a posteriori estimation.**
- **This model is optimized alternatively in an iterative way to get the solutions of Color-Guided Depth map Super-Resolution (CGD-SR) task and Low-Brightness Color Image Enhancement (LBC-IE) task. The whole iterative optimization procedure is expanded as a joint model-driven unfolding network.**

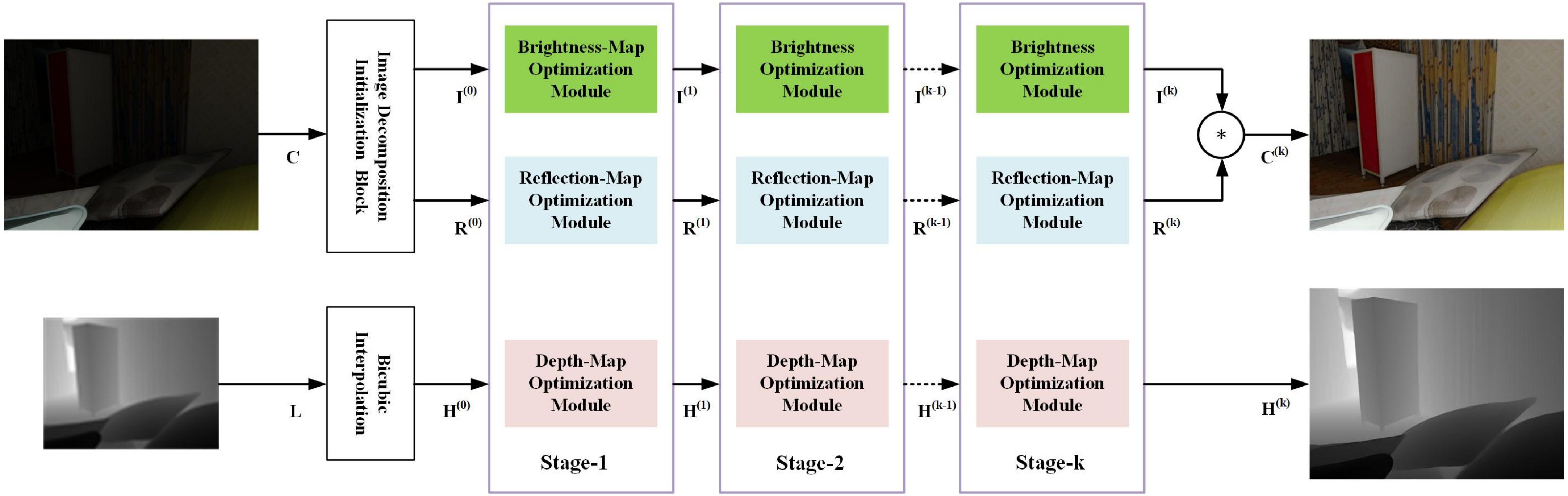

Fig. 2 The diagram of the proposed method

$$P(H,R,I|L,C)=\frac{1}{3}(P(L|H)\bullet P(H|R,I,C)+P(C|R)\bullet P(R|H,I,L)+P(C|I)\bullet P(I|H,R,C)) \quad (1)$$

$$\begin{aligned}\underset{H,R,I}{argmax}\, logP(H,R,I\mid L,C) &= \underset{H}{argmax}\, logP(L\mid H)+logP(H\mid R,I,C)\\ &+\underset{R}{argmax}\, logP(C\mid R)+logP(R\mid H,I,L)\\ &+\underset{I}{argmax}\, logP(C\mid I)+logP(I\mid H,R,L)\end{aligned} \quad (2)$$

$$\begin{aligned}\underset{H,R,I}{argmin}\, logP(H,R,I\mid L,C) &= \underset{H}{argmin}\frac{1}{2}\left\|L-DKH\right\|_2^2+\alpha f_1(H\mid R,I,C)\\ &+\underset{R}{argmin}\frac{1}{2}\left\|C-R\bullet I\right\|_2^2+\beta f_2(R\mid H,I,L)\\ &+\underset{I}{argmin}\frac{1}{2}\left\|C-R\bullet I\right\|_2^2+\gamma f_3(I\mid H,R,L)\end{aligned} \quad (3)$$

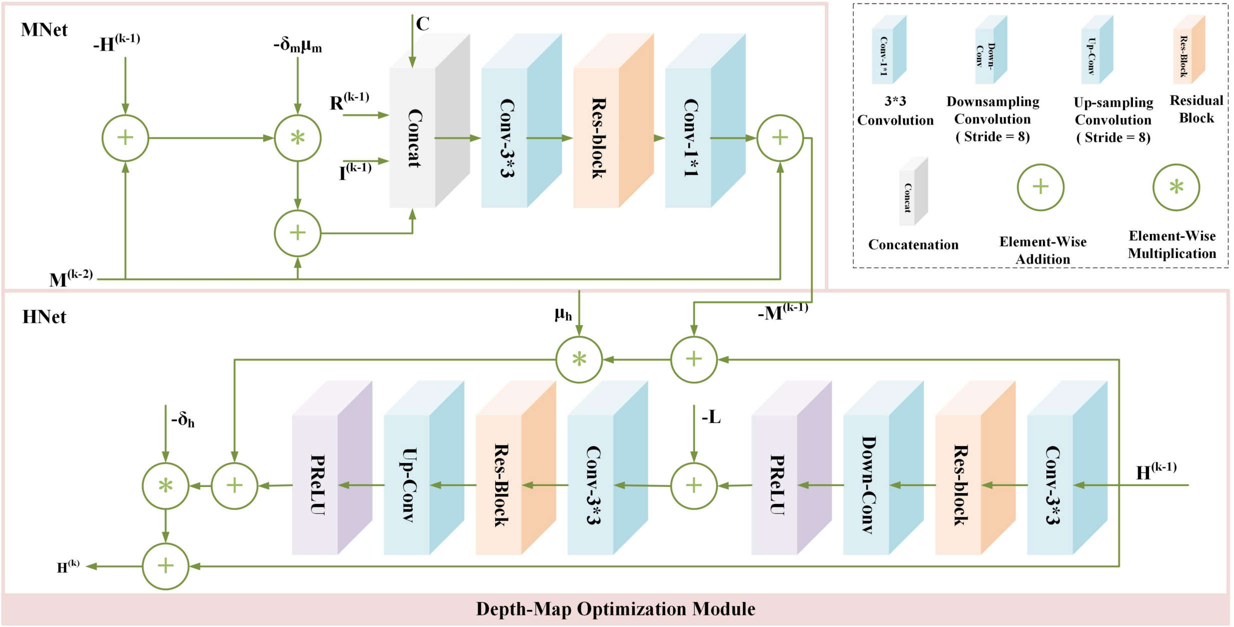

Fig. 3 The network structure of depth-map optimization module

$$M^{(k-1)} = prox_{f_1(R^{(k-1)}, I^{(k-1)}, C)}\left(M^{(k-2)} - \delta_m \mu_m \left(M^{(k-2)} - H^{(k-1)}\right)\right) \tag{4}$$

$$H^{(k)} = H^{(k-1)} - \left(\delta_h (DK)^T \left(DKH^{(k-1)} - L\right) + \mu_h \delta_h \left(H^{(k-1)} - M^{(k-1)}\right)\right) \tag{5}$$

02 SED METHOD

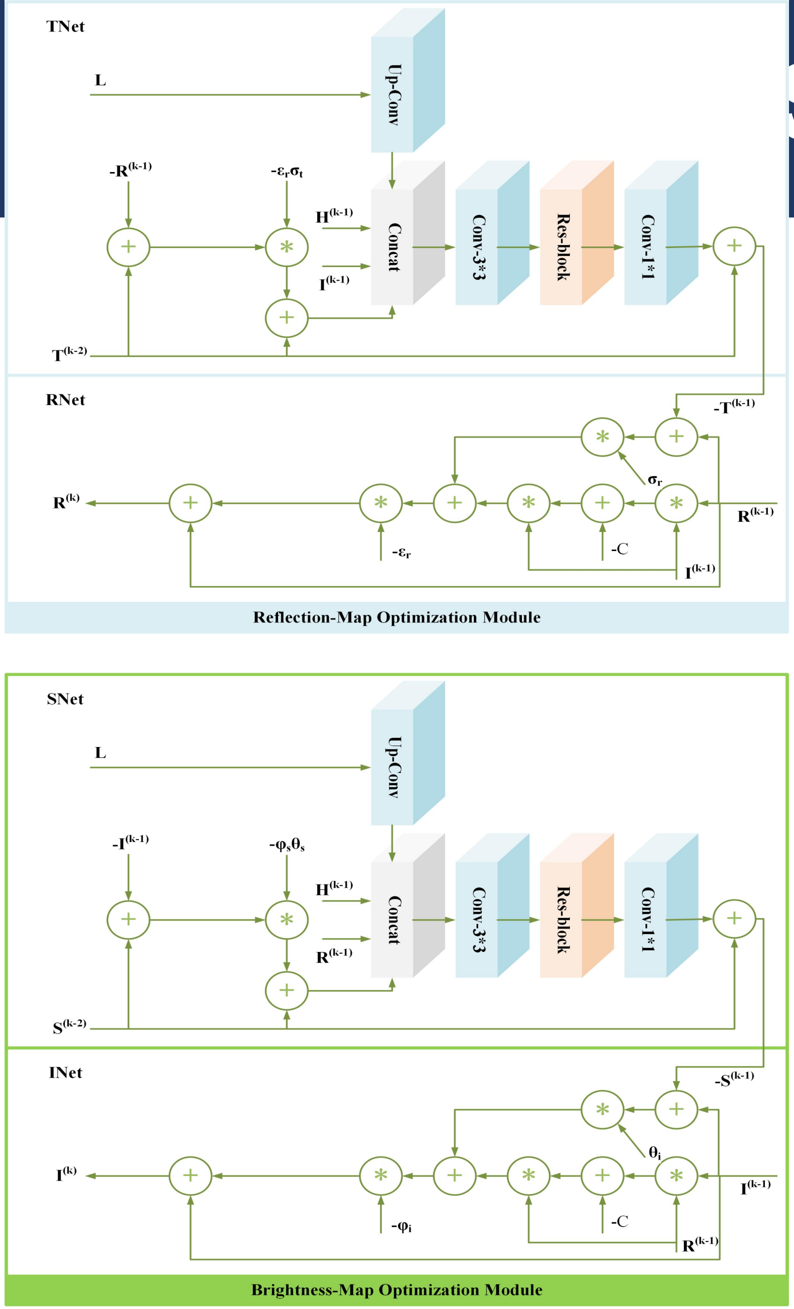

Fig. 4 The network structure of reflection-map optimization module and brightness-map optimization module

$$T^{(k-1)} = prox_{f_2(H^{(k-1)},I^{(k-1)},L)}\left(T^{(k-2)} - \varepsilon_t\sigma_t\left(T^{(k-2)} - R^{(k-1)}\right)\right) \quad (6)$$

$$R^{(k)} = R^{(k-1)} - \left(\varepsilon_r I^{(k-1)}\left(R^{(k-1)}I^{(k-1)} - C\right) + \varepsilon_r\sigma_r\left(R^{(k-1)} - T^{(k-1)}\right)\right) \quad (7)$$

$$S^{(k-1)} = prox_{f_3(H^{(k-1)},R^{(k-1)},L)}\left(S^{(k-2)} - \varphi_s\theta_s\left(S^{(k-2)} - I^{(k-1)}\right)\right) \quad (8)$$

$$I^{(k)} = I^{(k-1)} - \left(\varphi_i R^{(k-1)}\left(I^{(k-1)}R^{(k-1)} - C\right) + \varphi_i\theta_i\left(I^{(k-1)} - S^{(k-1)}\right)\right) \quad (9)$$

03

EXPERIMENTAL RESULTS

03 EXPERIMENTAL RESULTS

Table 1. The comparison of quantitative low brightness enhancement results in terms of PSNR and SSIM on LLRGBD synthetic dataset. (The higher the PSNR and SSIM value, the better the performance)

Method	PSNR	SSIM
DLN	19.163	0.8069
KinD	16.352	0.7274
Retinex	16.257	0.7040
SCI	23.121	0.8098
URetinex	18.667	0.7712
Zero[	23.487	0.8499
Our-4×	25.073	<u>0.8665</u>
Our-8×	**25.282**	**0.8705**
Our-16×	<u>25.148</u>	0.8649

Table 2. The comparison of quantitative depth SR results in terms of RMSE and MAD on LLRGBD synthetic dataset. (The lower the RMSE and MAD value, the better the performance)

Method	4×	8×	16×
DLN+JGF	1.7715/0.4647	2.4843/0.6840	3.7760/1.1572
Zero+JGF	1.7964/0.4816	2.5268/0.7086	3.8661/1.1838
KinD+JGF	1.8020/0.4815	2.5393/0.7069	3.8458/1.1909
Retinex+JGF	1.7972/0.4761	2.5409/0.7006	3.8349/1.1847
SCI+JGF	1.8047/0.4854	2.5378/0.7137	3.9109/1.1923
Our	**1.4960/0.3237**	**2.3441/0.5493**	**3.3144/1.0502**

Table 2: The comparison of quantitative depth SR results (in terms of RMSE and MAD) on LLRGBD synthetic dataset. (The lower the RMSE and MAD value, the better the performance)

Method	4×	8×	16×
DLN+PMBANet	1.7994/0.4079	2.5035/0.5999	3.7657/1.0952
Zero+PMBANet	1.7994/0.4079	2.5040/0.6005	<u>3.7551/1.0895</u>
KinD+PMBANe	1.7994/0.4079	2.5055/0.6013	3.7797/1.1016
Retinex+PMBANet	1.7994/0.4079	2.5096/0.6014	3.7560/1.0891
SCI+PMBANet	1.7994/0.4079	2.5026/0.6001	3.7560/1.0891
URetinex+PMBANet	1.7994/0.4079	2.5062/0.6006	3.7648/1.0987
Our	**1.4960/0.3237**	**2.3441/0.5493**	**3.3144/1.0502**

THANK YOU