NEURAL INFORMATION PROCESSING SYSTEMS

CST-Net

Rethinking Nighttime Image Deraining via Learnable Color Space Transformation

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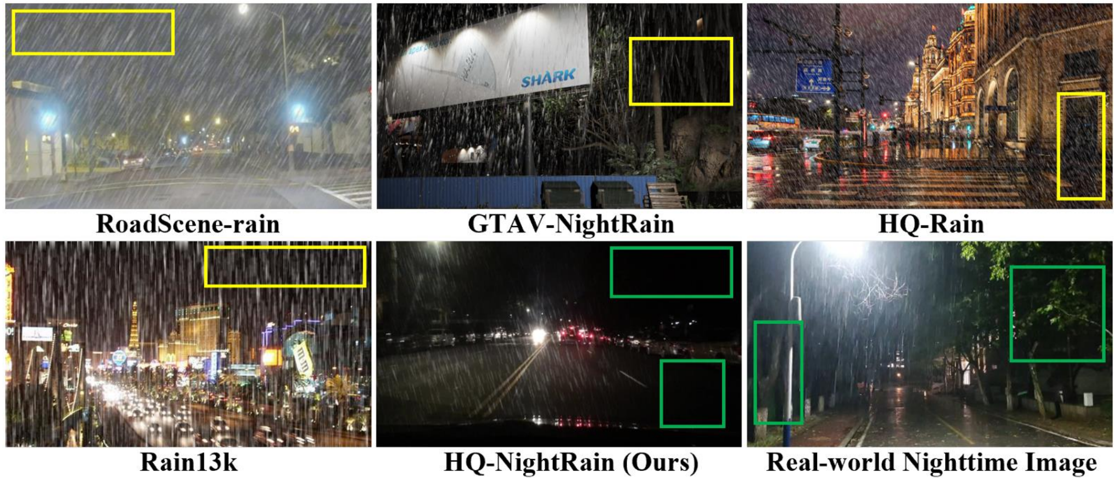
Introduction

- Nighttime image deraining remains challenging due to complex illumination conditions and the lack of realistic datasets. We introduce **HQ-NightRain**, a high-quality benchmark featuring visually harmonious and realistic nighttime rain scenes by coupling rain distribution with illumination variations.

- To effectively handle nighttime rain removal, we propose **CST-Net**, a Color Space Transformation Network that integrates a learnable color space converter and implicit illumination guidance. The converter adaptively shifts rain-related information into the Y channel, where nighttime rain effects are more distinguishable, enhancing rain removal performance. Extensive experiments demonstrate that CST-Net achieves superior deraining results on HQ-NightRain and public benchmarks, highlighting both the value of the dataset and the effectiveness of the proposed method.



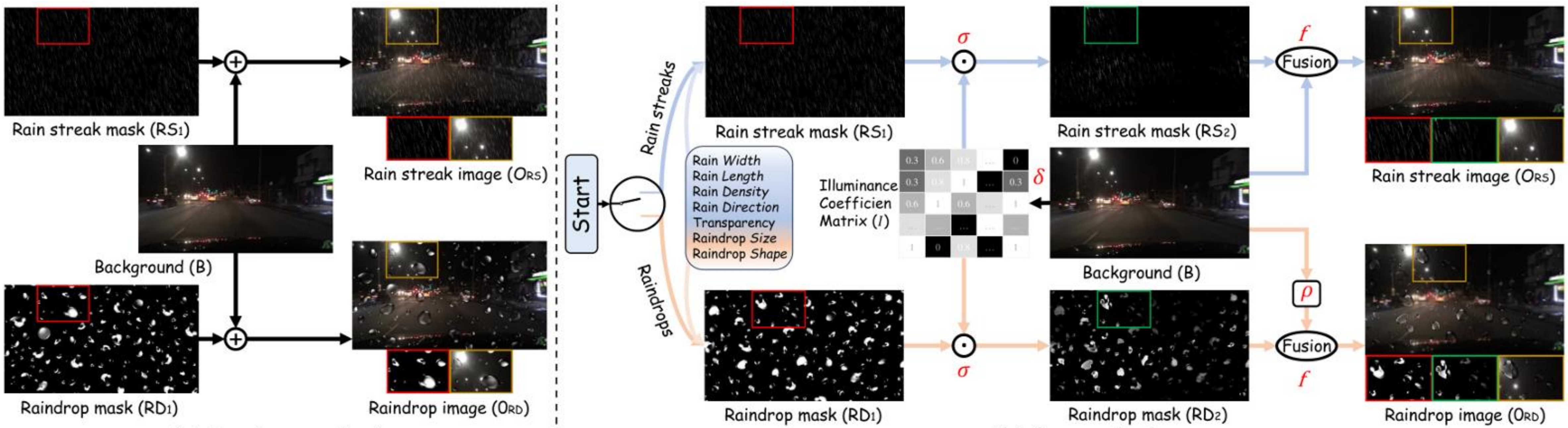
HQ-NightRain

➢ **Motivation:**

Existing nighttime deraining datasets suffer from unrealistic and globally uniform rain distributions due to the simple linear superposition of rain and background.

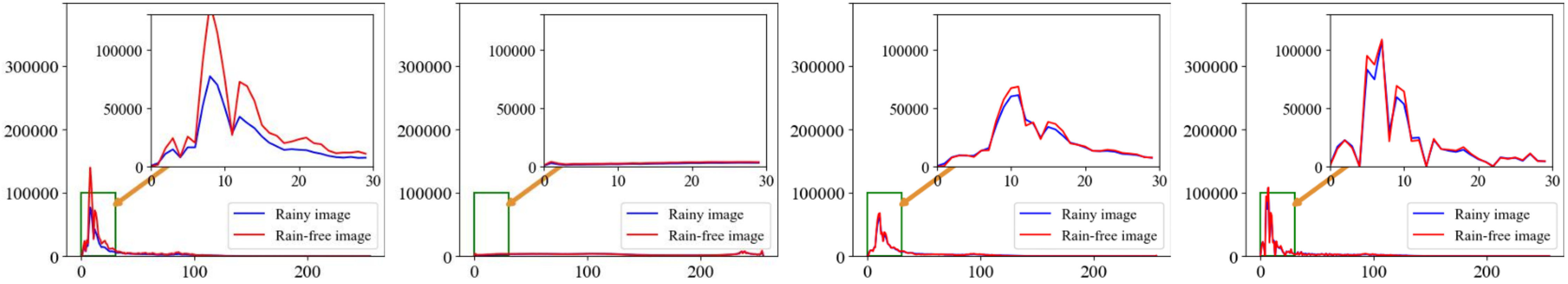
➢ **HQ-NightRain:**

Introduces a new rain synthesis pipeline that associates rain masks with illumination coefficients, making rain effects more visible near light sources and less visible in dark regions.



(a) Previous method (b) Our method

CST-Net



(a) Y (YCbCr); Nighttime (b) Y (YCbCr); Daytime (c) V (HSV); Nighttime (d) L (LAB); Nighttime

Histograms compare rainy and rain-free images across color spaces. The **Y** channel in YCbCr shows the most significant difference at nighttime, indicating that rain information is concentrated in the Y channel. In contrast, the daytime Y channel and other spaces (HSV-V, LAB-L) show weaker responses. This finding motivates our CST-Net to perform deraining primarily in the Y channel for effective nighttime rain removal.

CST-Net

Traditional color space Transformation

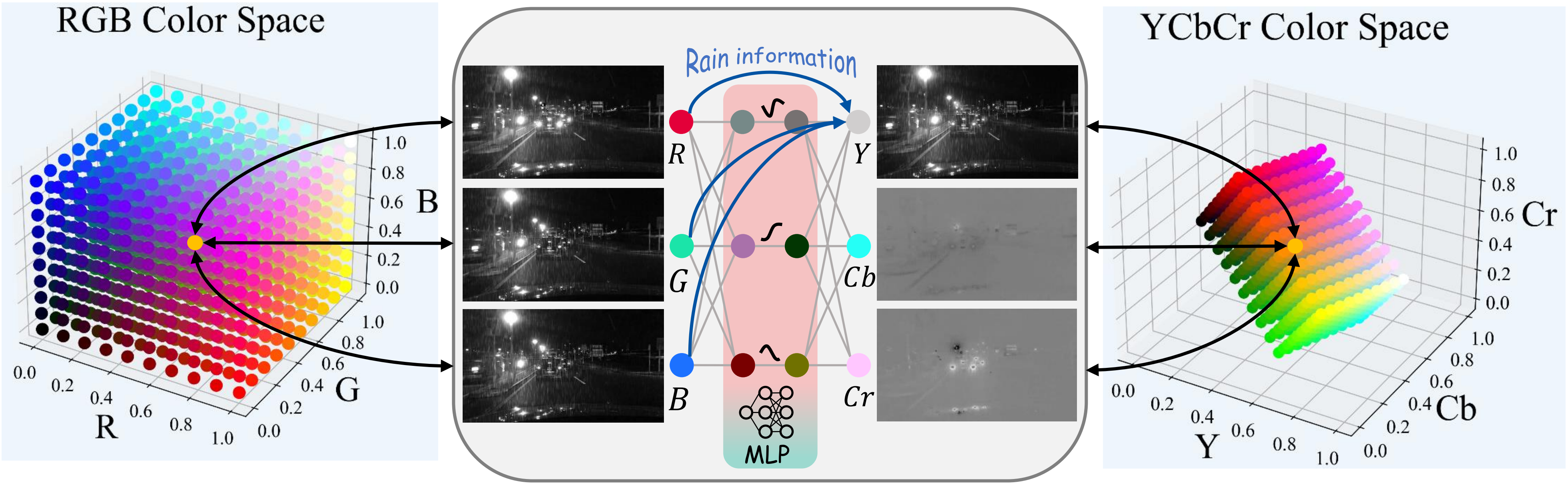
Fixed weight

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.169 & -0.331 & 0.5 \\ 0.5 & -0.419 & -0.081 \end{bmatrix} \circ \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

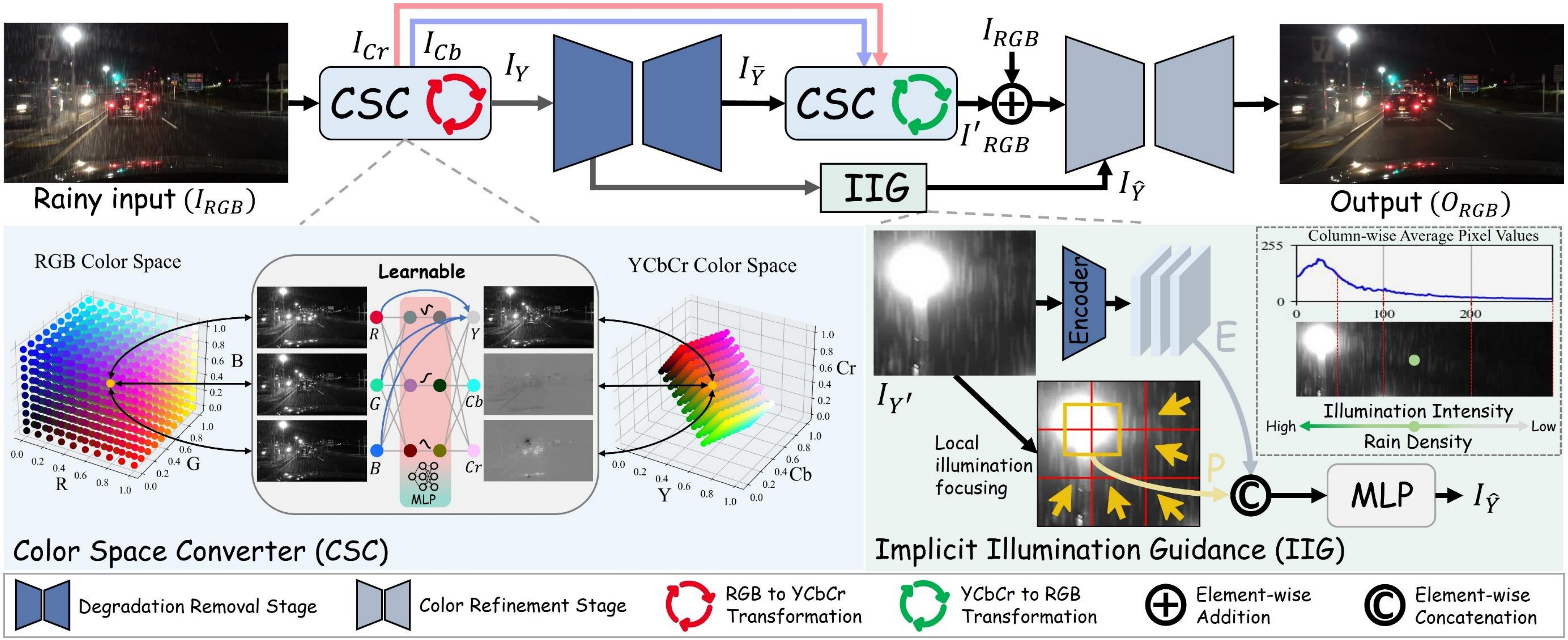
Learnable Color Space Transformation

$$\mathbf{\Phi} = \{\varphi_{i,j}\} = \begin{bmatrix} \varphi_{1,1} & \varphi_{1,2} & \varphi_{1,3} \\ \varphi_{2,1} & \varphi_{2,2} & \varphi_{2,3} \\ \varphi_{3,1} & \varphi_{3,2} & \varphi_{3,3} \end{bmatrix}$$

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \mathrm{MLP}(\mathbf{\Phi}) \circ \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$



CST-Net



I_{Cr}
I_{Cb}
I_Y
CSC
$I_{\bar{Y}}$
CSC
I_{RGB}
I'_{RGB}
IIG
$I_{\hat{Y}}$
Rainy input (I_{RGB})
Output (O_{RGB})
RGB Color Space
Learnable
YCbCr Color Space
R
G
B
Y
Cb
Cr
MLP
Color Space Converter (CSC)
Encoder
E
P
Column-wise Average Pixel Values
255
0
100
200
Illumination Intensity
High
Low
Rain Density
$I_{Y'}$
Local illumination focusing
MLP
$I_{\hat{Y}}$
Implicit Illumination Guidance (IIG)
Degradation Removal Stage
Color Refinement Stage
RGB to YCbCr Transformation
YCbCr to RGB Transformation
Element-wise Addition
Element-wise Concatenation

Experiments

Table 1: Quantitative evaluations on the HQ-NightRain dataset and GTAV-NightRain [53] dataset. The best and second-best values are **blod** and underlined.

Datasets	HQ-NightRain									GTAV-NightRain			Average		
	RS			RD			SD								
Methods	PSNR	SSIM	LPIPS	PSNR	SSIM	LPIPS	PSNR	SSIM	LPIPS	PSNR	SSIM	LPIPS	PSNR	SSIM	LPIPS
PReNet	38.5849	0.9842	0.0234	32.0029	0.9432	0.1709	34.8373	0.9698	0.0730	36.6332	0.9703	0.0609	35.5146	0.9669	0.0821
RCDNet	37.7537	0.9788	0.0357	31.8923	0.9357	0.1842	32.7796	0.9512	0.1452	37.0809	0.9703	0.0638	34.8766	0.9590	0.1072
SPDNet	40.0493	0.9865	0.0188	31.4772	0.9361	0.1638	39.0373	0.9825	0.0405	38.0175	0.9748	0.0462	37.1453	0.9700	0.0673
IDT	42.4204	0.9918	0.0116	33.6176	0.9522	0.1350	38.4873	0.9843	0.0361	37.5592	0.9744	0.0493	38.0211	0.9757	0.0580
Restormer	41.8844	0.9907	0.0145	33.7958	0.9503	0.1289	40.1790	0.9884	0.0266	38.1271	0.9772	0.0403	38.4966	0.9767	0.0526
SFNet	41.4805	0.9920	0.0139	33.6059	0.9465	0.1268	40.3011	0.9875	**0.0243**	37.5404	0.9738	0.0470	38.2320	0.9749	0.0530
DRSformer	42.8107	0.9922	0.0126	33.8452	0.9491	0.1348	40.4315	**0.9886**	0.0251	37.8722	0.9766	0.0415	38.7399	0.9766	0.0535
RLP	40.4093	0.9885	0.0167	29.9728	0.9204	0.1744	31.1297	0.9709	0.0855	34.9621	0.9600	0.0945	34.1185	0.9600	0.0928
MSGNN	27.7182	0.8846	0.2429	24.5151	0.8244	0.4946	27.6339	0.9078	0.2884	34.7993	0.9562	0.1180	28.6666	0.8933	0.2860
NeRD-Rain	42.7139	0.9923	0.0109	33.8313	0.9500	0.1391	39.6834	0.9855	0.0320	37.8137	0.9738	0.0530	38.5106	0.9754	0.0588
CST-Net (Ours)	**42.8850**	**0.9924**	**0.0100**	**33.9395**	**0.9523**	**0.1239**	**40.4984**	0.9881	0.0248	**38.9378**	**0.9786**	**0.0320**	**39.0652**	**0.9778**	**0.0477**

Experiments

Table 2: Quantitative evaluations on the RealRain-1k [28] dataset and RainDS-real [33] dataset.

Datasets	RealRain-1k						RainDS-real								
	RealRain-1k-L			RealRain-1k-H			RS			RD			RDS		
Methods	PSNR	SSIM	LPIPS	PSNR	SSIM	LPIPS	PSNR	SSIM	LPIPS	PSNR	SSIM	LPIPS	PSNR	SSIM	LPIPS
PReNet	27.1939	0.8881	0.3941	23.4536	0.7977	0.5036	23.0181	0.6857	0.3267	19.5145	0.6270	0.3980	18.7119	0.5900	0.4454
RCDNet	27.1157	0.8862	0.3965	23.4234	0.7964	0.5050	23.6687	0.6763	0.3540	21.5567	0.6246	0.4106	20.6816	0.5859	0.4615
MPRNet	27.1221	0.8867	0.4007	23.5270	0.7933	0.5097	23.9263	0.6872	0.3231	21.9558	0.6339	0.3831	21.0407	0.5972	0.4338
IDT	26.9428	0.8873	0.3912	23.4492	0.7997	0.4977	24.1806	**0.7088**	0.2950	21.8945	**0.6551**	0.3635	21.0991	**0.6219**	0.4021
SFNet	26.7338	0.8861	0.3912	23.2136	0.7984	0.4964	24.4064	0.6971	0.3000	22.0831	0.6510	0.3521	21.0251	0.6095	0.4159
DRSformer	27.2100	0.8885	0.3932	23.7299	0.8049	0.4970	24.8096	0.7052	0.2833	21.7949	0.6415	0.3658	20.7358	0.6040	0.4046
RLP	26.8646	0.8801	0.4026	23.1733	0.7898	0.5119	22.7828	0.6601	0.3411	20.5325	0.6136	0.3909	19.6163	0.5694	0.4521
MSGNN	25.5384	0.8692	0.4337	22.0136	0.7702	0.5354	22.7039	0.6572	0.3427	19.3446	0.6168	0.3735	18.2088	0.5637	0.4476
NeRD-Rain	27.1613	**0.8895**	0.3867	23.6547	0.8046	0.4915	24.2879	0.6870	0.2912	22.0290	0.6329	0.3523	21.1359	0.5943	0.4095
CST-Net (Ours)	**27.3064**	0.8891	**0.3805**	**23.8114**	**0.8062**	**0.4877**	**25.0456**	0.7065	**0.2715**	**22.7280**	0.6499	**0.3479**	**22.0070**	0.6175	**0.3816**

Experiments

Table 4: Ablation analysis of different variants in our method, including two-stage network pipeline, other color space transformation (RGB, HSV, HSL, YUV and YCbCr), learnable color space converter (CSC), and implicit illumination guidance (IIG).

Methods	Network Pipeline		Other Color Space Transformation					CSC		IIG	Metrics	
	Stage1	Stage2	RGB	HSV	HSL	YUV	YCbCr	Fixed	Learnable		PSNR	SSIM
$\text{Ours}_{\text{w/o Stage2\&w/ YCbCr\&w/ CSC\&w/o IIG}}$	✔	✗	✗	✗	✗	✗	✔	✗	✔	✗	35.0858	0.9650
$\text{Ours}_{\text{w/o Stage1\&w/ YCbCr\&w/ CSC\&w/o IIG}}$	✗	✔	✗	✗	✗	✗	✔	✗	✔	✗	36.4385	0.9740
$\text{Ours}_{\text{w/ Stage1+2\&w/ YCbCr\&w/ CSC\&w/o IIG}}$	✔	✔	✗	✗	✗	✗	✔	✗	✔	✗	39.8767	0.9866
$\text{Ours}_{\text{w/ Stage1+2\&w/ RGB\&w/o CSC\&w/o IIG}}$	✔	✔	✔	✗	✗	✗	✗	✗	✗	✗	38.7507	0.9838
$\text{Ours}_{\text{w/ Stage1+2\&w/ HSV\&w/o CSC\&w/o IIG}}$	✔	✔	✗	✔	✗	✗	✗	✔	✗	✗	39.0317	0.9843
$\text{Ours}_{\text{w/ Stage1+2\&w/ HSL\&w/o CSC\&w/o IIG}}$	✔	✔	✗	✗	✔	✗	✗	✔	✗	✗	39.1613	0.9844
$\text{Ours}_{\text{w/ Stage1+2\&w/ YUV\&w/o CSC\&w/o IIG}}$	✔	✔	✗	✗	✗	✔	✗	✔	✗	✗	39.1932	0.9846
$\text{Ours}_{\text{w/ Stage1+2\&w/ YCbCr\&w/o CSC\&w/o IIG}}$	✔	✔	✗	✗	✗	✗	✔	✔	✗	✗	39.5959	0.9857
Ours	✔	✔	✗	✗	✗	✗	✔	✗	✔	✔	**40.4984**	**0.9881**

Experiments

(a) Rainy input (b) Ground truth (c) IDT [28] (d) Restormer [35] (e) DRSformer [5] (f) NeRD-Rain [7] (g) Ours

Figure 5. Derained results on the HQ-NightRain (first row) and GTAV-NightRain [36] (second row) datasets. Zoom in for a better view.

Experiments

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(a) Rainy input (b) RCDNet [25] (c) IDT [28] (d) Restormer [35] (e) DRSformer [5] (f) NeRD-Rain [7] (g) Ours

Figure 6. Derained results on the real-world nighttime rainy image from the RealRain-1k [18] dataset. Zoom in for a better view.

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Thanks for watching!

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