Supplementary Materials for "A Semi-supervised Nighttime Dehazing Baseline with Spatial-Frequency Aware and Realistic Brightness Constraint"

1. Abbreviations, Notations and Dataset Settings

The abbreviations, notations and dataset settings can be found at Table 1, Table 2 and Table 3, respectively.

2. Code Implementations

The details for training and inference can be found in "readme.md" inside our code. The source code is provided in https://github.com/Xiaofeng-life/SFSNiD.

3. Visualization of Frequency Spectrums

Here, the Frequency Spectrum Dynamic Aggregation (FSDA) module proposed in this paper is visualized in both frequency and spatial domain. Figure 1 shows the amplitude spectrums, phase spectrums and feature maps. According to the amplitude spectrums, it can be concluded that the residual feature map obtained after filtering contains sufficient high-frequency components. This means that the residual feature map obtained after filtering can effectively enhance the edges and details of the original feature map.

4. More Ablation Studies

Table 4 and 5 show the ablation experimental results for the three datasets. The conclusions obtained are generally consistent with the Main Paper.

5. More Real-world Dehazing Results

The Main Paper shows the dehazing results of two scenes on the real-world nighttime haze (RWNH) [1] dataset. Figure 4, 5 and 6 show more results on the RWNH. The synthetic training data used by all algorithms comes from [3]. The results obtained by most algorithms suffer from missing textures or unrealistic lighting. The visual results show that the dehazing method (Ours) proposed in this paper obtains better details and has more realistic brightness.

6. More Synthetic Images Dehazing Results

Visual results on the synthetic dataset UNREAL-NH [3] are shown in the Main Paper. Figure 7, 8, 9, 10, 11, 12, 13 and 14 show dehazed results on synthetic nighttime haze datasets GTA5, NHCL, NHCM, NHCD, NHM, NHR , NightHaze and YellowHaze, respectively. The visual results obtained by the proposed algorithm are competitive with state-of-the-art algorithms.

7. More Results obtained by Imaging Model (IM) and Game Engine (GE) datasets

As we discussed in the Main Paper, that is, "The dehazed image obtained under IM dataset has obvious haze and glow, while the dehazed image obtained under GE dataset has unrealistic brightness.". Figure 3 shows the dehazed images obtained by multiple state-pf-the-art dehazing algorithms on the IM and GE datasets. The conclusion given in Figure 3 is consistent with the Main Paper.

8. Results under Different Window Sizes

Figure 2 gives real-world dehazed images under different window sizes. The results show that different window sizes have little impact on the dehazing results. Therefore, we empirically set the window size to 16.

Table 1. Abbreviations.

Abbreviation	Meaning
FSDA	Frequency Spectrum Dynamic Aggregation
FDP	Frequency Domain Projection
BLP	Bidomain Local Perception
BNM	Bidomain Nonlinear Mapping
SFII	Spatial and Frequency Information Interaction
LBM	Local Brightness Map

Table 2. Basic notations.

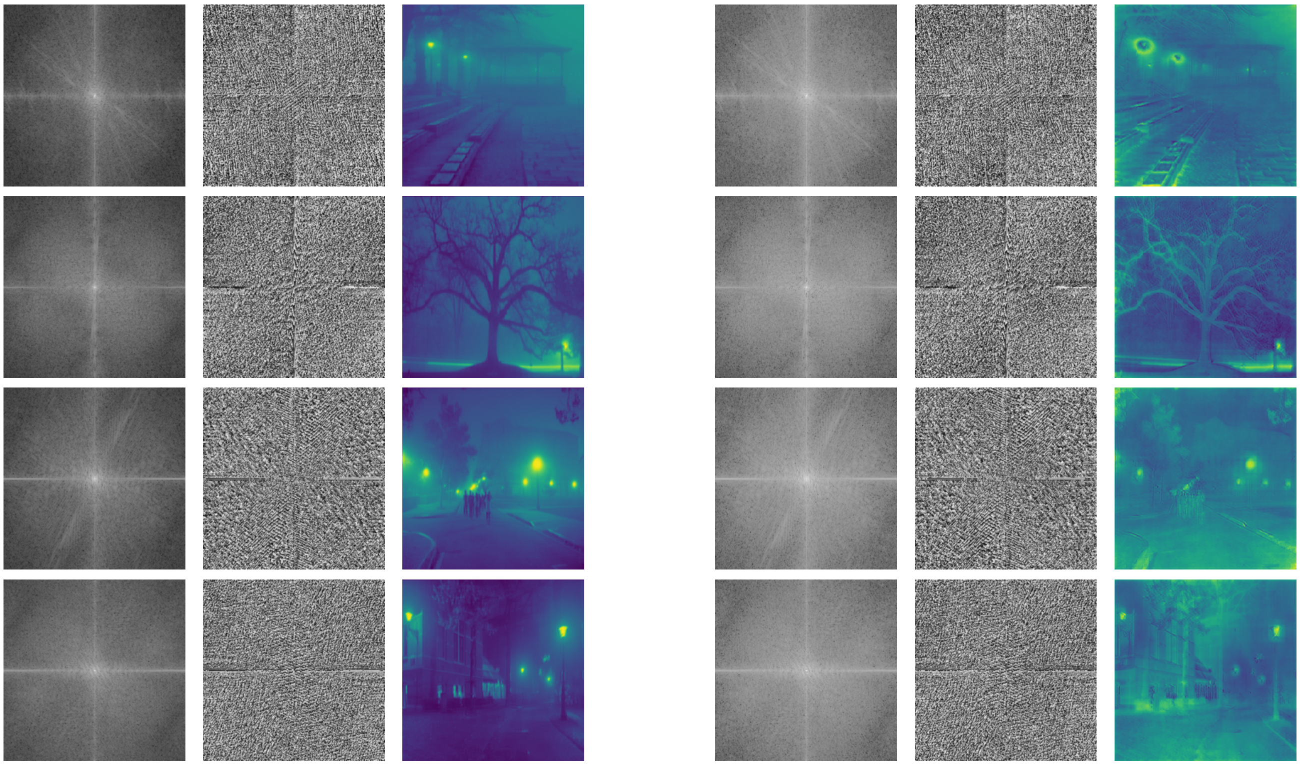
Notation	Meaning
H	height of the image
W	width of the image
C	channels of the image
$\widetilde{H}$	height of the feature map
$\widetilde{W}$	width of the feature map
$\widetilde{C}$	channels of the feature map
X	hazy domain
Y	haze-free domain
$\mathcal{D}_X$	synthesized hazy images
$\mathcal{D}_Y$	synthesized haze-free images
$\mathcal{R}_X$	real-world hazy images
$\mathcal{R}_Y$	real-world haze-free images
$\varpi(\cdot)$	global average pooling
$\sigma(\cdot)$	LeakyReLU
$\delta(\cdot)$	sigmoid
$sf(\cdot)$	softmax
k	kernel size
t	stride
s	scale, where $s \in \{0, 1, 2\}$
z	feature map
$\Psi^s(\cdot)$	network at scale s
$\mathcal{F}$	Fourier transformation

Table 3. Dataset settings.

Dataset	train	test
NHR	8073	897
NHM	290	60
NHCD	498	52
NHCL	498	52
NHCM	498	52
NightHaze	9874	1070
YellowHaze	8649	913
GTA5	787	77
UNREAL-NH	8064	1008

Table 4. More ablation studies on the SFII.

Methods	NHR					UNREAL-NH					NHM				
	$R1$	$R2$	$R3$	$R4$	Ours	$R1$	$R2$	$R3$	$R4$	Ours	$R1$	$R2$	$R3$	$R4$	Ours
SSIM ↑	0.979	**0.980**	0.975	0.965	0.978	0.848	0.858	0.851	0.845	**0.862**	0.892	0.899	0.882	0.753	**0.905**
PSNR ↑	33.087	33.177	32.197	29.921	**33.180**	25.353	25.808	25.642	24.301	**25.907**	22.050	23.070	21.605	21.677	**23.705**



amplitude | phase | feature map

(a) before frequency domain filtering

amplitude | phase | residual feature map

(b) after frequency domain filtering

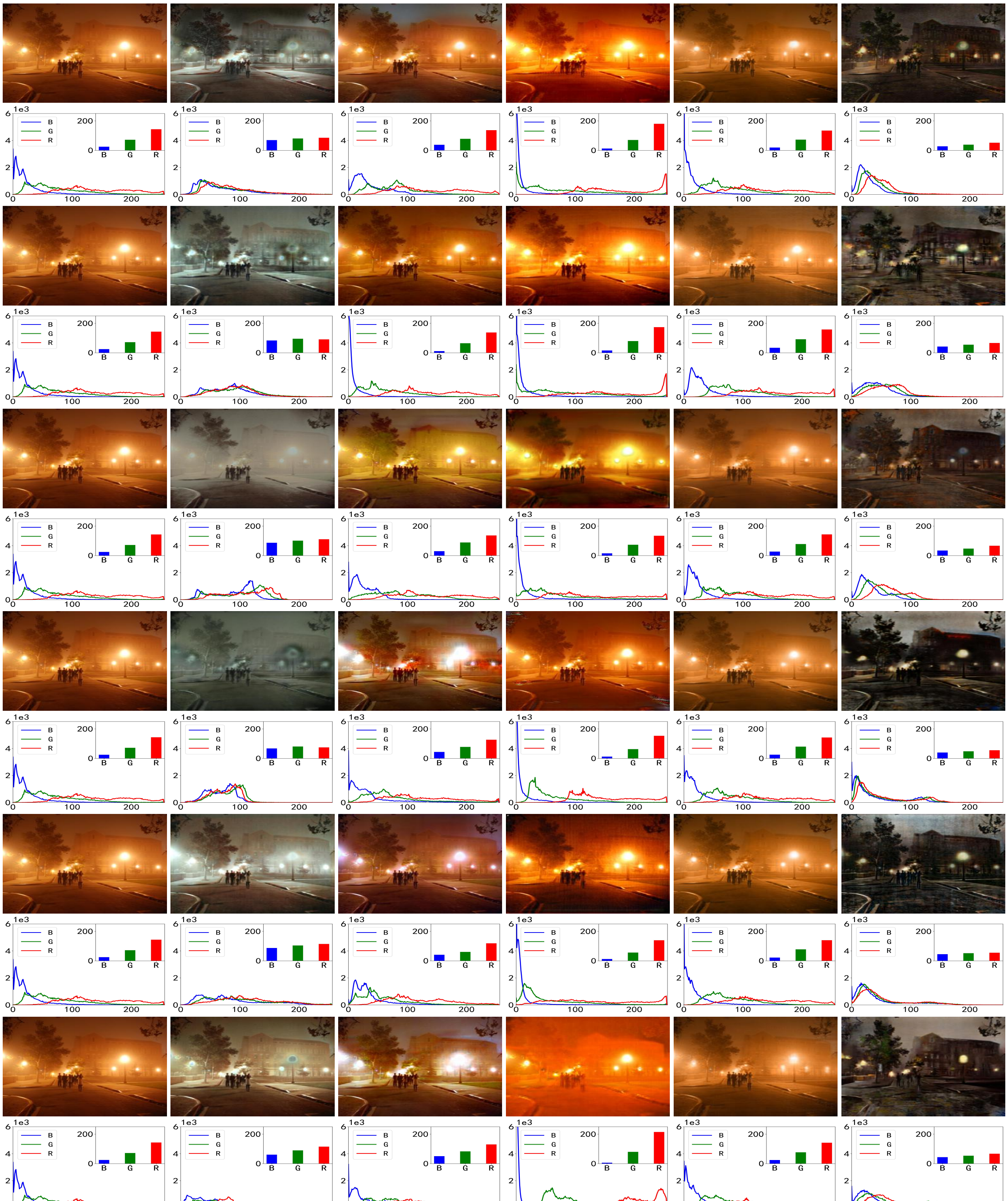
Figure 1. The amplitude spectrums, phase spectrums and feature maps.

(a) Hazy (b) $\gamma^0 = 4$ (c) $\gamma^0 = 8$ (d) $\gamma^0 = 16$ (e) $\gamma^0 = 32$ (f) $\gamma^0 = 48$

Figure 2. Visual results under different window size γ^s (for $\mathcal{L}_B$), where $s \in \{0, 1, 2\}$ and $\gamma^2 = \frac{\gamma^1}{2} = \frac{\gamma^0}{4}$.

Table 5. More ablation studies on the scale loss and frequency loss.

Methods	NHR				UNREAL-NH				NHM			
	$S1$	$S2$	$S3$	Ours	$S1$	$S2$	$S3$	Ours	$S1$	$S2$	$S3$	Ours
SSIM ↑	**0.978**	**0.978**	0.975	**0.978**	0.854	0.851	0.816	**0.862**	0.902	0.904	0.890	**0.905**
PSNR ↑	32.88	33.074	32.722	**33.180**	25.601	25.134	24.464	**25.907**	23.352	23.198	23.482	**23.705**



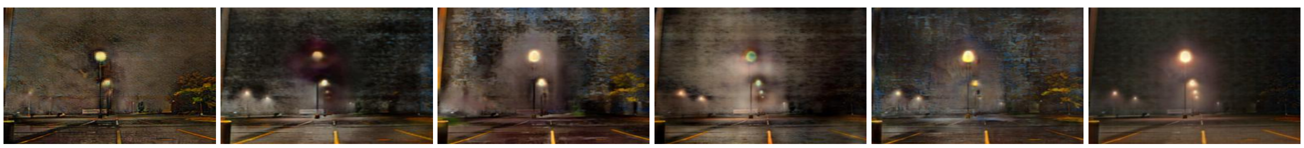
(a) Hazy (b) IM-NHCD [5] (c) IM-NHR [5] (d) IM-NightHaze [2] (e) IM-YellowHaze [2] (f) GE-UNREAL-NH [3]

Figure 3. Visualization of real-world dehazed images, where the "IM-" and "GE-" denote the dehazed results obtained by training on imaging model (IM) and game engine (GE) simulated datasets, respectively. The dehazing algorithms from top to down are GD, MSBDN, 4KDehazing, DeHamer, FSDGN and DF, respectively.

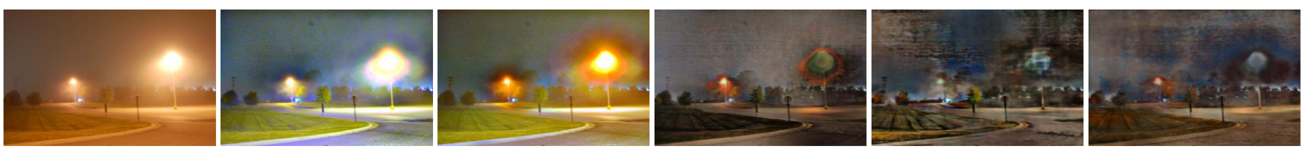
(a) Hazy (b) MRP (c) OSFD (d) GD (e) MSBDN (f) 4KDehazing

(g) AECRNet (h) DeHamer (i) DF (j) MITNet (k) Fourmer (l) Ours

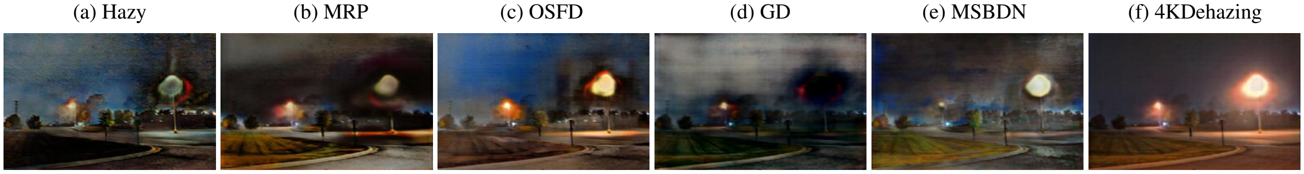
(a) Hazy (b) MRP (c) OSFD (d) GD (e) MSBDN (f) 4KDehazing



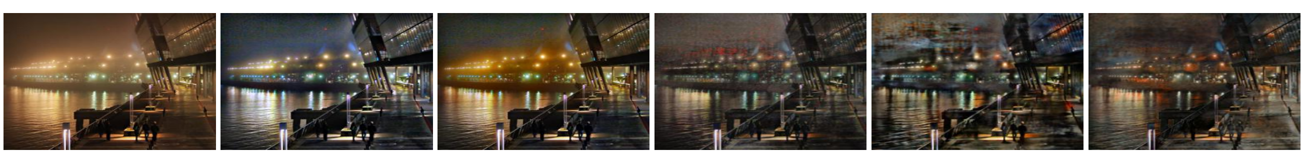
(g) AECRNet (h) DeHamer (i) DF (j) MITNet (k) Fourmer (l) Ours



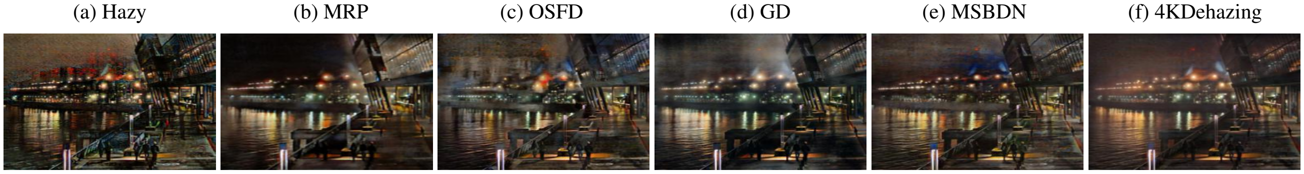
(a) Hazy (b) MRP (c) OSFD (d) GD (e) MSBDN (f) 4KDehazing



(g) AECRNet (h) DeHamer (i) DF (j) MITNet (k) Fourmer (l) Ours

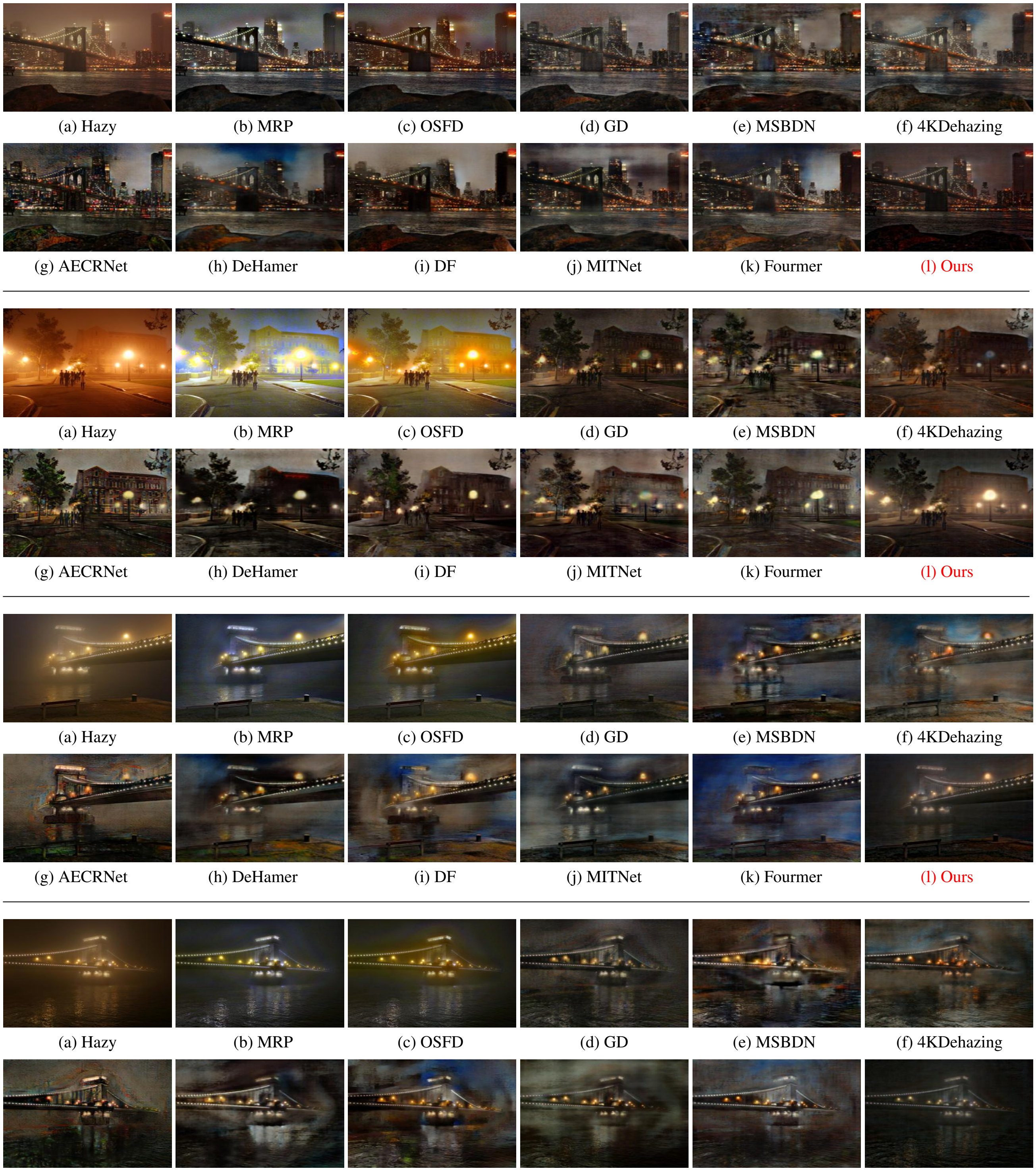


(a) Hazy (b) MRP (c) OSFD (d) GD (e) MSBDN (f) 4KDehazing



(g) AECRNet (h) DeHamer (i) DF (j) MITNet (k) Fourmer (l) Ours

Figure 4. Visual results on real-world nighttime haze (RWNH) [1] dataset.



(a) Hazy (b) MRP (c) OSFD (d) GD (e) MSBDN (f) 4KDehazing
(g) AECRNet (h) DeHamer (i) DF (j) MITNet (k) Fourmer (l) Ours

(a) Hazy (b) MRP (c) OSFD (d) GD (e) MSBDN (f) 4KDehazing
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(a) Hazy (b) MRP (c) OSFD (d) GD (e) MSBDN (f) 4KDehazing
(g) AECRNet (h) DeHamer (i) DF (j) MITNet (k) Fourmer (l) Ours

(a) Hazy (b) MRP (c) OSFD (d) GD (e) MSBDN (f) 4KDehazing
(g) AECRNet (h) DeHamer (i) DF (j) MITNet (k) Fourmer (l) Ours

Figure 5. Visual results on real-world nighttime haze (RWNH) [1] dataset.

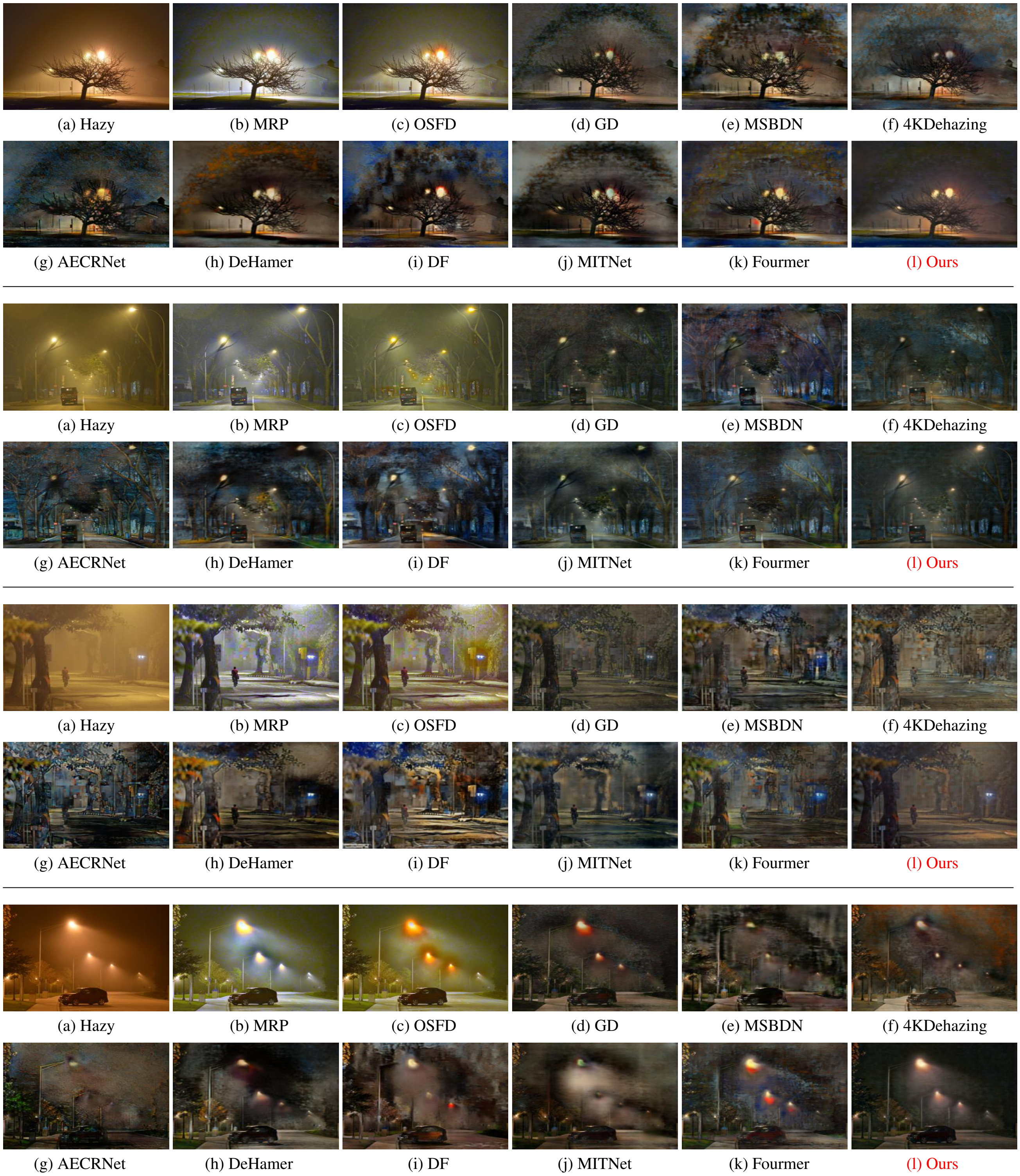


Figure 6. Visual results on real-world nighttime haze (RWNH) [1] dataset.

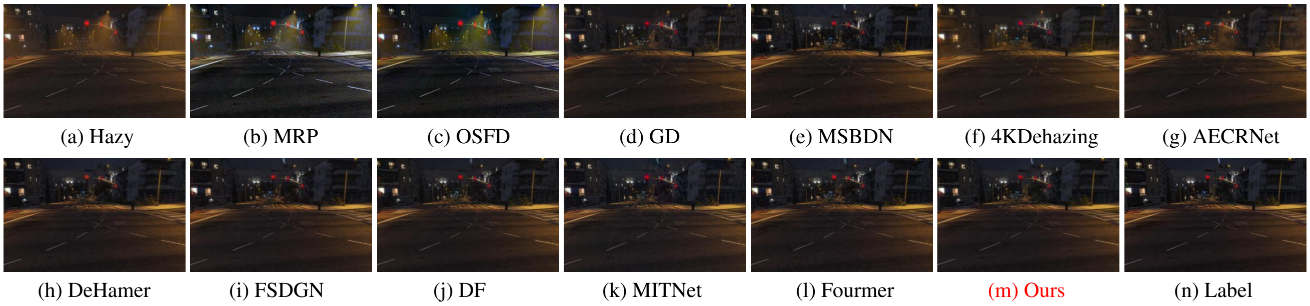


Figure 7. Visual results on synthetic dataset GTA5 [4].

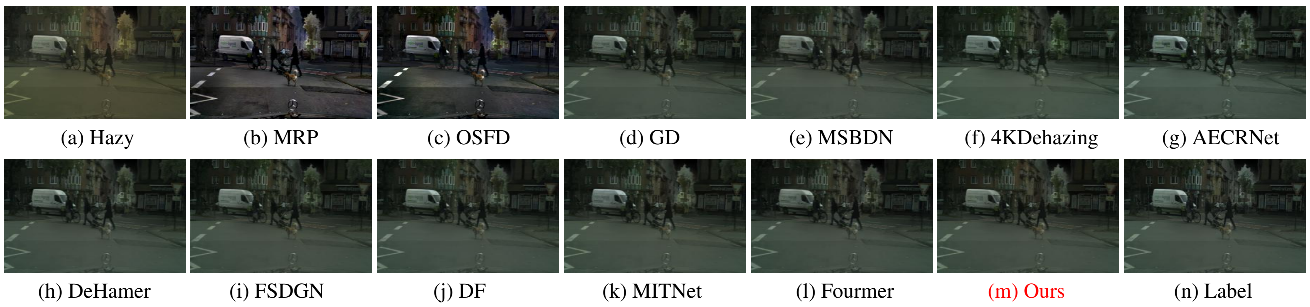


Figure 8. Visual results on synthetic dataset NHCL [5].

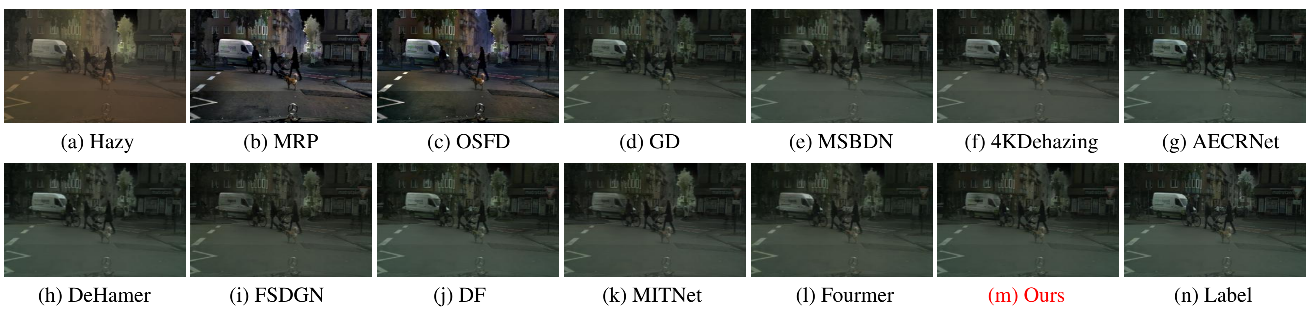


Figure 9. Visual results on synthetic dataset NHCM [5].

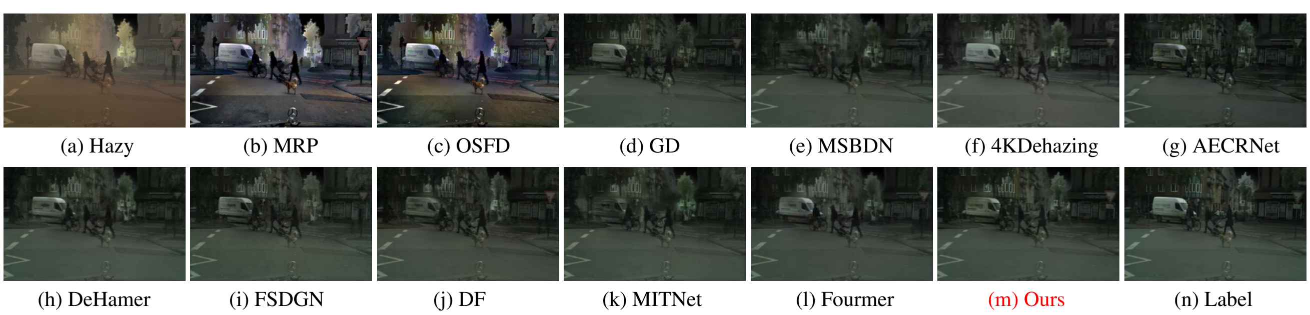
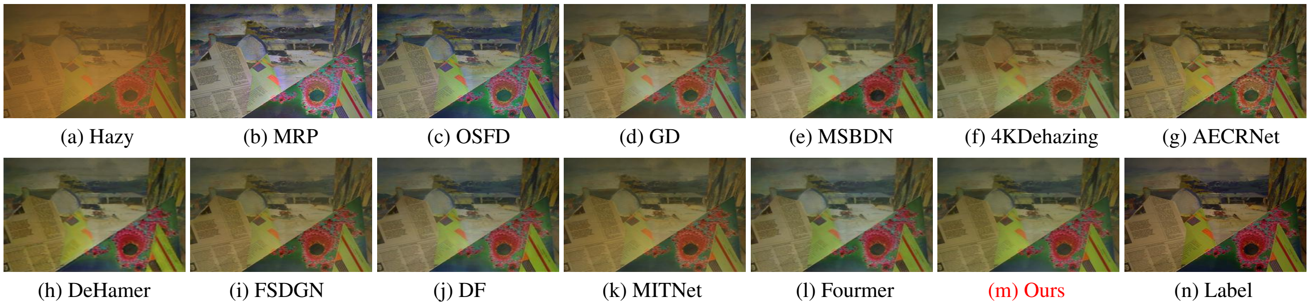


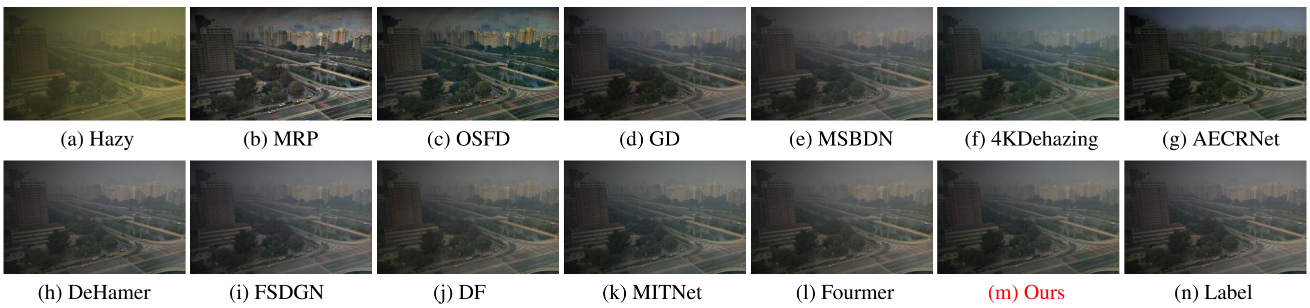
Figure 10. Visual results on synthetic dataset NHCD [5].



(a) Hazy (b) MRP (c) OSFD (d) GD (e) MSBDN (f) 4KDehazing (g) AECRNet

(h) DeHamer (i) FSDGN (j) DF (k) MITNet (l) Fourmer (m) Ours (n) Label

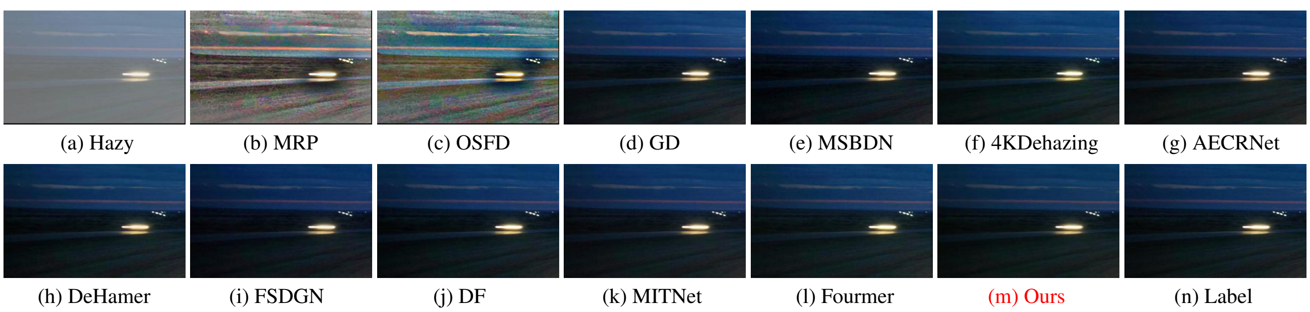
Figure 11. Visual results on synthetic dataset NHM [5].



(a) Hazy (b) MRP (c) OSFD (d) GD (e) MSBDN (f) 4KDehazing (g) AECRNet

(h) DeHamer (i) FSDGN (j) DF (k) MITNet (l) Fourmer (m) Ours (n) Label

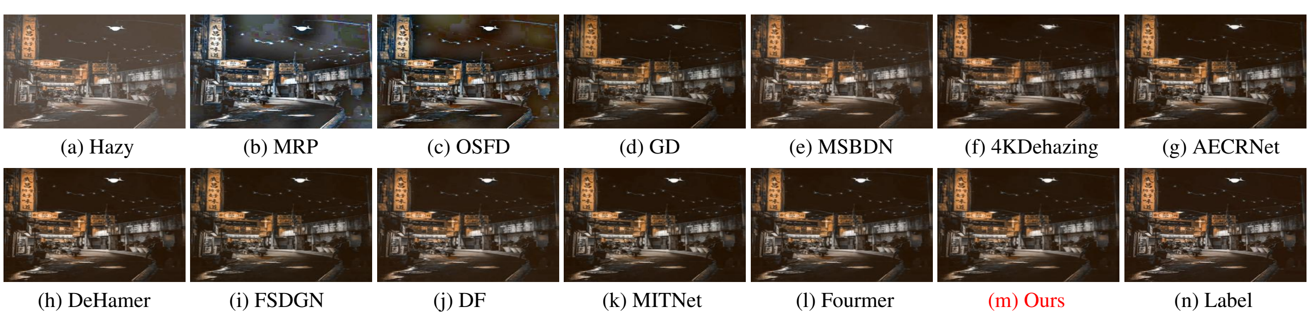
Figure 12. Visual results on synthetic dataset NHR [5].



(a) Hazy (b) MRP (c) OSFD (d) GD (e) MSBDN (f) 4KDehazing (g) AECRNet

(h) DeHamer (i) FSDGN (j) DF (k) MITNet (l) Fourmer (m) Ours (n) Label

Figure 13. Visual results on synthetic dataset NightHaze [2].



(a) Hazy (b) MRP (c) OSFD (d) GD (e) MSBDN (f) 4KDehazing (g) AECRNet

(h) DeHamer (i) FSDGN (j) DF (k) MITNet (l) Fourmer (m) Ours (n) Label

Figure 14. Visual results on synthetic dataset YellowHaze [2].

References

[1] Yeying Jin, Beibei Lin, Wending Yan, Wei Ye, Yuan Yuan, and Robby T Tan. Enhancing visibility in nighttime haze images using guided apsf and gradient adaptive convolution. In *ACM International Conference on Multimedia*, 2023. 1, 5, 6, 7

[2] Yinghong Liao, Zhuo Su, Xiangguo Liang, and Bin Qiu. Hdp-net: Haze density prediction network for nighttime dehazing. In *Pacific Rim Conference on Multimedia*, pages 469–480, 2018. 4, 9

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