Supplementary Materials for “Depth Information Assisted Collaborative Mutual Promotion Network for Single Image Dehazing”

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1. Parameter Selection and Analysis

In the main body of this paper, we set both parameters α and β in Eq. (1) to 1. Here, we use the SOTS-indoor dataset to analyze the effectiveness of $\alpha = 1$ and $\beta = 1$ by changing one while fixing the other. Figure 1 illustrates the PSNR curves when each parameter changes.

$$\ell_{dehaze} = \alpha \|\boldsymbol{A}_{e,r} \odot (\boldsymbol{u}^* - \boldsymbol{u})\|_1 + \beta \sum_{i=1}^{n} \lambda_i \frac{\|VGG_i(\boldsymbol{u}) - VGG_i(\Phi(\tilde{\boldsymbol{u}}^*, \omega_d))\|_1}{\|VGG_i(\tilde{\boldsymbol{u}}^*) - VGG_i(\Phi(\tilde{\boldsymbol{u}}^*, \omega_d))\|_1} \tag{1}$$

It is observed from Figure 1(a) that the proposed method performs well within the range of $\alpha \in [0.75, 1.25]$, and the PSNR reaches its peak when $\alpha = 1$. Consequently, we set $\alpha = 1$. On the other hand, as shown in Figure 1(b), when β changes within $[0.75, 1.50]$, the performance is relatively high, and achieves the best when $\beta = 1$. Therefore, we set $\beta = 1$ throughout the experiment.

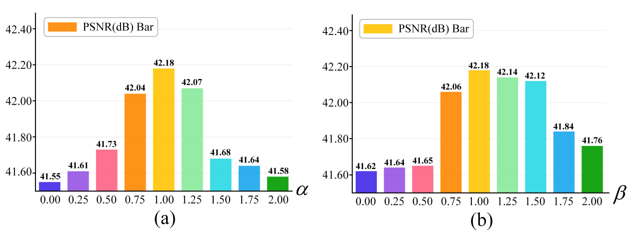

Figure 1. Parameter analysis on the SOTS-indoor dataset. PSNR curves with α and β.

2. Computational Complexity Analysis

In this section, we analyze the computational complexity of the comparative methods from three aspects: the quantity of model parameters, FLOPs, and the time required for testing. The results are listed in Table 1. The test time is the duration required for the model to process an image measuring 460×620 pixels. As indicated in Table 1, the parameter quantity and FLOPs of our model are moderate. The test time for our model is 0.117 second, indicating a relatively fast and acceptable inference speed. Consequently, our model can be practically deployed and applied following training.

3. Experiments on Real-world Datasets

The real-world Dense-Haze [1] and NH-Haze [2] datasets are used for image dehazing in real scenarios. The Dense-Haze dataset serves as the image dehazing challenge of NTIRE2019, consisting of 55 densely hazy images with paired clear images. The NH-Haze dataset, employed in the NTIRE2020 image dehazing challenge, contains 55 pairs of non-uniformly hazy images and their corresponding clear versions. In each dataset, the last 5 images are reserved for testing, while the remaining images are used for training.

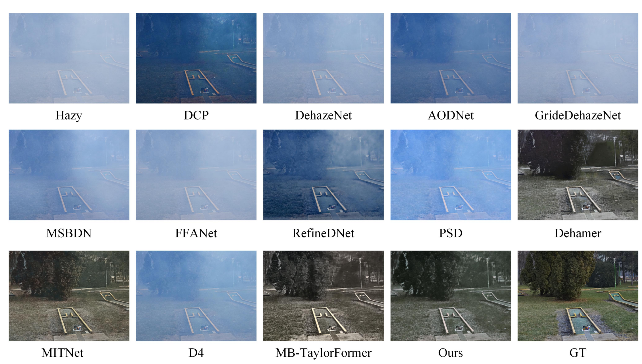

Figure 2. Visual comparison on Dense-Haze dataset.

To verify the generalizability of the proposed method, we conduct comparative experiments with existing methods on the real-world Dense-Haze and NH-Haze datasets. It is well-established that dehazing from real-world hazy images is inherently more challenging than that from synthetic hazy images. This increased difficulty stems from the typical characteristics of real-world haze, which tends to be denser and exhibits a non-uniform distribution. The dehazing results obtained by different methods on the Dense-Haze and NH-Haze datasets are shown in Figure 2 and Figure 3, respectively. From Figure 2, one can observe that

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Table 1. Performance comparison of the different methods on the quantity of model parameters , FLOPs and test time.

Methods	AECR-Net [15]	PSD [4]	MAXIM-2S [14]	Dehamer [6]	D4 [16]	Dehazeformer [13]	C2PNet [18]	MB-TaylorFormer [11]	MITNet [12]	Ours
Parameters(M)	2.61	6.21	14.10	135.45	10.7	25.44	7.17	7.43	2.49	7.16
FLOPs(G)	26.10	143.91	216.00	24.47	2.25	139.85	460.95	44.05	17.13	62.89
Test time (s)	0.006	0.559	0.641	0.170	-	0.328	0.929	1.163	0.049	0.117

Table 2. Performance of the proposed method is compared with that of state-of-the-art methods on real-world datasets (Dense-Haze and NH-Haze). Best values are in bold.

Methods	Dense-Haze					NH-Haze				
	PSNR↑	SSIM↑	NIQE↓	PIQE↓	FADE↓	PSNR↑	SSIM↑	NIQE↓	PIQE↓	FADE↓
DCP [7]	11.01	0.4165	5.2502	15.0944	2.7647	10.57	0.5196	5.2502	5.0944	0.7647
DehazeNet [3]	9.48	0.4383	6.5778	7.9937	2.6119	16.62	0.5238	2.8354	5.2104	0.6675
AOD-Net [8]	12.82	0.4683	6.2253	10.3068	1.9741	15.40	0.5693	2.8416	5.5681	0.3620
GridDehazeNet [9]	14.96	0.5326	7.0555	10.7274	4.3710	10.07	0.3986	2.8246	5.6275	0.7486
MSBDN [5]	15.13	0.5551	6.6765	9.8121	3.1787	19.23	0.7056	2.6862	5.2017	0.7423
FFA-Net [10]	12.22	0.4440	6.8754	20.1206	1.1549	19.87	0.6915	2.6624	5.7624	1.0356
RefineDNet [17]	12.91	0.4584	5.8663	11.4998	1.1159	12.91	0.4584	2.8067	5.9807	0.4605
PSD [4]	9.73	0.4345	5.4040	10.9304	1.6434	10.32	0.5274	2.8556	5.0698	0.4563
Dehamer [6]	16.22	0.5602	6.5784	56.5955	1.3626	20.66	0.6844	2.9575	8.0992	0.3883
D4 [16]	11.49	0.4821	6.1627	14.8036	2.2183	12.66	0.5072	2.5849	5.7850	0.5359
Dehazeformer [13]	16.29	0.5100	–	–	–	20.47	0.7310	–	–	–
C2PNet [18]	16.88	0.5728	–	–	–	–	–	–	–	–
MB-TaylorFormer [11]	16.44	0.5660	5.8181	21.1580	1.1907	–	–	–	–	–
MITNet [12]	16.97	0.6056	6.0711	35.8864	1.8673	**21.26**	0.7122	3.0026	10.1390	0.3624
Proposed	**17.00**	**0.6101**	**5.1017**	**6.7368**	**1.0696**	20.46	**0.7963**	**2.5186**	**4.9142**	**0.3535**

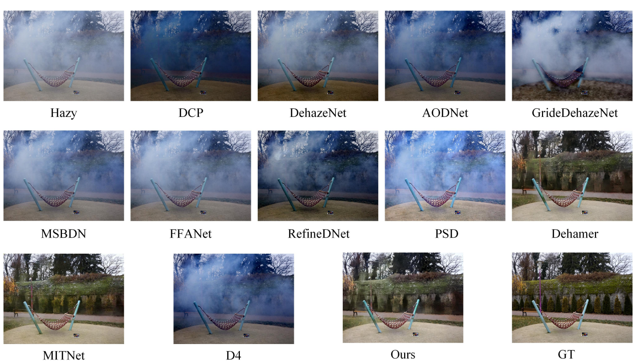


Figure 3. Visual comparison on NH-Haze dataset.

on the Dense-Haze dataset, the dehazing results of compared methods is not satisfactory except Dehamer, MB-TaylorFormer, MITNet and the proposed method. However, those four methods mentioned above provide limited dehazing outcomes for dense haze, where the haze residues and color distortion still exist to some extent. From Figure 3, it can be seen that the dehazing results are poor on NH-Haze dataset, with the exception of Dehamer, MITNet and the proposed method.

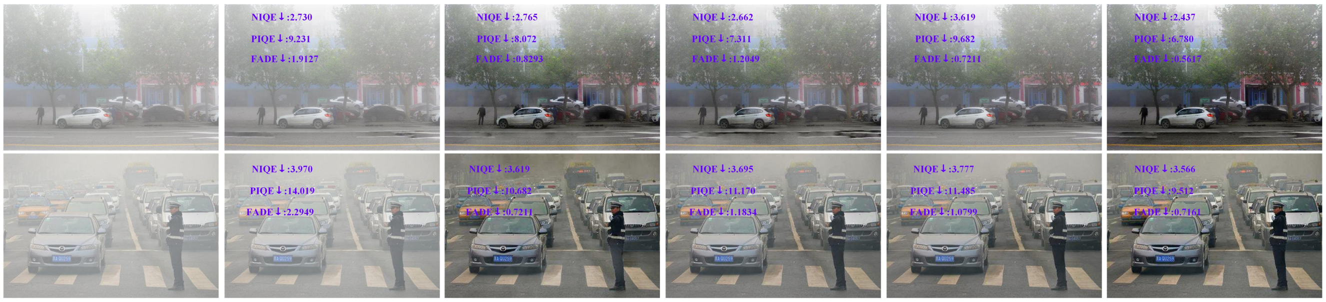
Furthermore, the quantitative evaluation results on the Dense-Haze and NH-Haze datasets are presented in Table 2. It can be seen that the proposed method achieves the best values across all evaluation metrics when applied to the Dense-Haze dataset. For the NH-Haze dataset, the proposed method attains either the best or comparable scores on the evaluation metrics. The experimental results demonstrates the effectiveness of proposed method and its superiority over the state-of-the-art methods.

4. Additional Dehazing Results on Real-world Images

To further validate the generalizability of the proposed model, we present the dehazing results of different methods on real-world dense hazy images, as shown in Figure 4. From Figure 4, it is evident that our method yields the most favorable visual results and also attains the best values in quantitative evaluation metrics.

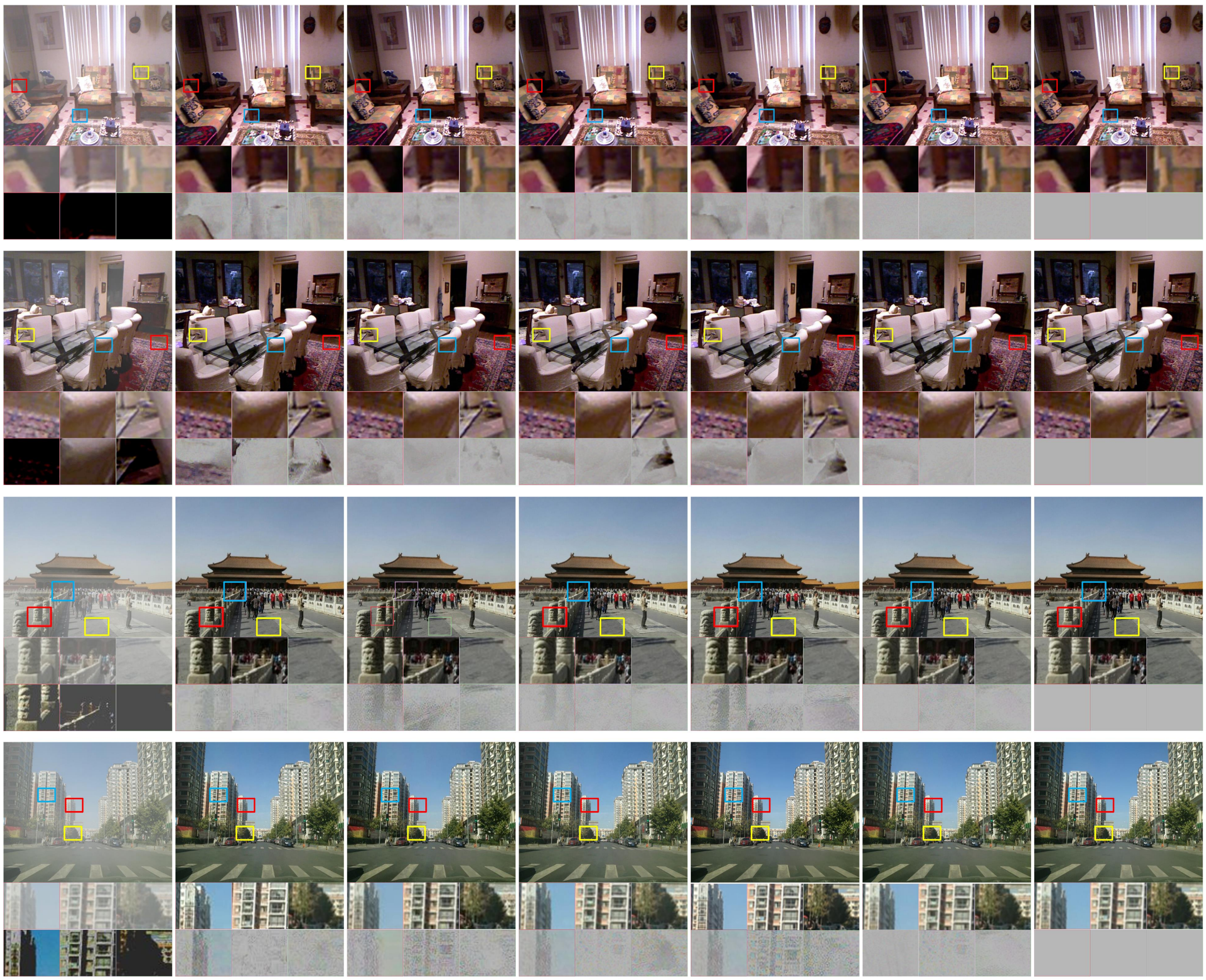
5. Additional Dehazing Results on Synthetic Datasets

For a comprehensive comparison, we provide additional dehazing results of different methods on the SOTS-indoor and SOTS-outdoor datasets in Figure 5. Moreover, to facilitate the visual comparison, we display the difference maps between the enclosed areas and their GTs. The difference maps reveal that the proposed method yields consistently superior dehazing results compared to other methods.



Hazy image **MB-Taylorformer** **Dehazeformer** **MITNet** **C2PNet** **Ours**

Figure 4. Visual comparison on real-world dense hazy images.



Hazy Dehamer C2PNet MB-TaylorFormer MITNet Ours GT

Figure 5. Additional visual comparisons on SOTS-indoor and SOTS-outdoor.

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