1. Dataset and Experimental Setup

In this section, we describe more details of datasets and experimental setups for three image restoration tasks. Unless specified here, the hyper-parameters mentioned in the main text are adopted.

**Image Dehazing.** We evaluate the proposed network on both daytime and nighttime datasets. The daytime datasets include both synthetic (RESIDE [10]) and real-world (NH-HAZE [3], Dense-Haze [2], O-HAZE [4]) datasets.

The RESIDE [10] dataset contains two training subsets, i.e., indoor training set (ITS) and outdoor training set (OTS). ITS consists of 13990 hazy images generated from 1399 sharp images. OTS comprises 313950 hazy images produced from 8970 clean images. RESIDE [10] contains a testing subset, i.e., synthetic objective testing set (SOTS), which is composed of indoor and outdoor scenes, each including 500 hazy images. We evaluate the ITS-trained and OTS-trained models on SOTS-Indoor and SOTS-Outdoor datasets, respectively. The model is trained for 30 epochs on RESIDE-Outdoor with initial learning rate as $1e^{-4}$ and batch size as 8. On RESIDE-Indoor, the model is trained for 1000 epochs.

NH-HAZE [3] and Dense-Haze [2] both consist of 55 paired images, while O-HAZE [4] contains only 45 image pairs. For these real-world datasets, models are trained for 5000 epochs following [8] on $800 \times 1200$ patches with initial learning rate as $2e^{-4}$ and batch size as 2.

The nighttime dataset NHR [27] contains 16146 and 1794 image pairs for training and evaluation, respectively. The model is trained for 300 epochs with initial learning rate as $1e^{-4}$ and batch size as 8.

**Image Desnowing.** Snow100K [14], SRRS [5], and CSD [6] contain 50000, 15005, and 8000 image pairs for training, and 50000, 15005, and 2000 images for evaluation, respectively. Models are trained for 2000 epochs.

**Single-Image Defocus Deblurring.** As in previous methods [9, 21, 25], we choose the DPDD [1] dataset to demonstrate the efficacy of our method. We adopt the training strategy in [21] to train our model.

2. More Experimental Results

2.1. Image Motion Deblurring

For this task, we train and evaluate our model on the widely used GoPro [18] dataset with the initial learning rate as $1e^{-4}$ and batch size as 4. The model is trained for 3000 epochs. We deploy 20 residual blocks in each ResBlock. The results are presented in Table 1. Compared with other competitors, our method achieves a better trade-off between computation overhead and performance.

2.2. Image Denoising

We present the grayscale image denoising results in Table 2. The model is trained for 100 epochs on the same dataset as Restormer [10] and tested on BSD68 [16]. The initial learning rate is set as $1e^{-4}$ and batch size as 16.
ings while attenuating the simple regions such as the sky. The same conclusion can also be drawn for desnowing in highlights the edge information as marked by red arrows.

Table 3. Design choices of DSM. SSM*2 means we use two SSM successively.

<table>
<thead>
<tr>
<th>Method</th>
<th>SSM</th>
<th>SSM*2</th>
<th>FSM</th>
<th>FSM*2</th>
<th>SSM+FSM</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSNR</td>
<td>33.71</td>
<td>34.97</td>
<td>32.60</td>
<td>32.73</td>
<td>35.60</td>
</tr>
</tbody>
</table>

Table 4. Design choices of MResBlock. Share means the convolution parameters are shared among two branches.

We employ 24 residual block in each ResBlock to have the comparable complexity with other algorithms [25, 20]. As shown in the table, our CNN-based method outperforms the strong Transformer model Restormer [25] for all noise levels.

### 3. More Ablation Studies

The experimental settings remain identical with that of the ablation study section in the main text. 

**Design Choices of DSM.** We conduct experiments by using different combinations of SSM and FSM. As shown in Table 3, deploying two identical modules successively, the models obtain better performance than that of using single one. Our choice, employing dual-domain selection mechanism, produces the best performance.

In addition, we provide visualization comparisons between different designs to demonstrate the superiority of our method. As illustrate in Figure 1, using two SSM, the model focuses on degradation regions. The version with two FSM pays attention to edge signals. Our method only emphasizes signals that are difficult to recover, which facilitates high efficiency of our model.

**Design Choices of MResBlock.** In MResBlock, we split features and treat each component individually. During this process, convolution layers can be shared among two branches or not. As shown in Table 4, sharing parameters degrades performance by 0.34 dB. Therefore, we use separate convolutions in two branches for better performance.

**More Visual Examples of DSM.** Figure 2 and Figure 3 illustrate the effects of our DSM for defocus deblurring and desnowing, respectively. As shown in Figure 2, our spatial selection module (SSM) suppresses the simple regions, such as the trunk in the top image and the left stone in the bottom image. Our frequency selection module (FSM) highlights the edge information as marked by red arrows. The same conclusion can also be drawn for desnowing in Figure 3. Our modules accentuate the complicated buildings while attenuating the simple regions such as the sky.

### 4. More Visual Results

In this section, we provide more visual comparisons for three tasks: defocus deblurring (Figure 4), dehazing (Figure 5 and 6), and desnowing (Figure 7). The images produced by our models are visually closer to the ground-truth than those of other approaches.

**References**


Figure 1. Comparisons between different designs of DSM. Images are obtained from SOTS-Indoor [10] dataset.

Figure 2. Effectiveness of our DSM on defocus deblurring. Images are obtained from DPPD [1] dataset.

Figure 3. Effectiveness of our DSM on desnowing. Images are obtained from CSD [6] dataset.


Figure 4. Single-image defocus deblurring comparisons on the DPDD [1] dataset.


[16] David Martin, Charless Fowlkes, Doron Tal, and Jitendra Malik. A database of human segmented natural images and its application to evaluating segmentation algorithms and
Figure 5. Image dehazing comparisons on the Dense-Haze [2] dataset.


Figure 7. Image desnowing comparisons on the CSD [6] dataset.


