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Supplementary Material for “All in One Bad Weather removal using Fusion Search”

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Anonymous CVPR submission

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1. Real Rain Results Comparison

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We show the results of our method compared with other state of the art dedicated methods on real rain removal dataset [2] in Fig. 1. From the figure, one can see that our results can also remove rain streaks and rain veiling effects at the same time. In the second row of Fig. 1, although HRGAN [2] can recover the tree leaves on the branch, the restored tree leaves are incomplete and blur. However, in our result, we can recover the complete tree leaves as well as remove the strong rain streaks and rain veils.

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2. Real Snow Results Comparison

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We show the results of our method compared with other state of the art dedicated desnow methods on snow removal task in Fig. 3. The real snow data are from DesnowNet [5]. One can observe from the figure that [5]’s results have some tiny snow flakes left on the image, but ours result can remove most of the snow flakes.

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3. More Raindrop Results Comparison

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We also demonstrate more real raindrop removal results in Fig. 4 in addition to the results in our main paper. Since most of the method have already achieved quite good restoration results on this datasets, we have amplified the details in the red boxes in each image for better comparison. One can observe that although our method is trained on multiple domain bad weather data, our results can still outperforms the state of the art dedicated methods.

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4. Ablation Study on Search Ops

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In this ablation study, we examined the effectiveness of each component in the Fusion Search stage as shown in Table 1. Here, we can see that if we remove the residue operation and unveiling operation, the network performance reduces more compared with our full architecture variant in terms of PSNR. This is because these two operations have embedded the rain and rain veiling effect model, therefore,

Table 1: Ablation Study on our Fusion Search component in the proposed network. The evaluation is conducted on rain and fog removal tasks.

Method	Rainfog dataset [2]	
Metric	PSNR	SSIM
Concatenation	21.58	0.834
No unveiling operation	20.97	0.817
No residue operation	20.82	0.832
No self-attention operation	21.36	0.863
Dedicated Encoders	21.47	0.828
Full Architecture	21.92	0.865

the features extracted by fusion search part is more invariant to rain. To further study the advantage of fusion search, we also develop a multiple encoder network, each of which embeds the proposed operation according to the task, i.e. the rainfognet is contains decomposition operation, residue operation and unveiling operation. The performance of this network is also shown in Table 1 as “dedicated encoders”.

5. Study on clean input

In this paper, our objective is to design a solution that can work under multiple different weather environments without using extra weather detection. To that end, it is important to show that our network is still able to work under good weather condition so that a weather classifier is not necessary. In this case, we have tested clean images from multiple different scenes as shown in Fig. 2

6. Network Structure

We demonstrate the detailed architecture in Table 2. For the RainFogNet, we have adopted the chromatic pyramid in [3] denoted as “chromatic layer”.

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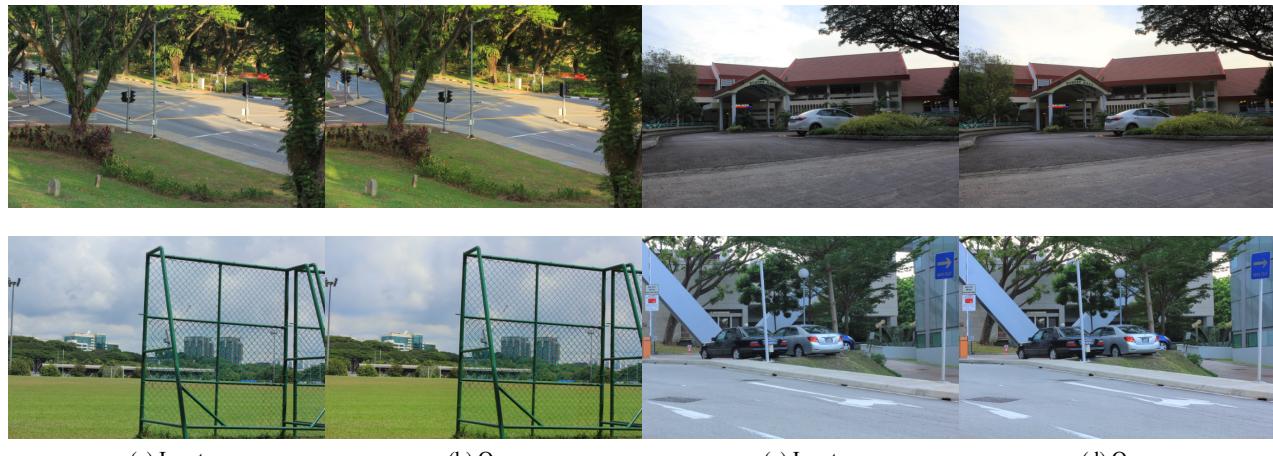
(a) input

(b) RESCAN [4]

(c) HRGAN [2]

(d) Ours

Figure 1: Raindrop removal results of our method compared with state of the art raindrop removal dedicated methods. (Zoom in to the red box to see details.)



(a) Input

(b) Ours

(c) Input

(d) Ours

Figure 2: Our results of clean input images. The PSNR value of these 4 image pairs are : 33.87dB, 34.44dB, 34.27dB, 33.84dB.

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(a) input

(b) DetailsNet [4]

(c) DesnowNet [5]

(d) Ours

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Figure 3: Snow removal results of our method compared with state of the art snow removal dedicated methods. (Zoom in to see the details.)

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(a) input

(b) AttentGAN[6]

(c) Quan et al. [7]

(d) Ours

(e) Ground Truth

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Figure 4: Raindrop removal results of our method compared with state of the art raindrop removal dedicated methods. (Zoom in to the red box to see details.)

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Table 2: The detailed architecture of the proposed all-in-one network.

Layers	Output Size	RainFogNet	SnowNet	RaindropNet
Conv2d	224×224	5×5 Chromatic Layer, stride 1	5×5 conv, stride 1	
Conv2d	112×112	3×3 Chromatic Layer, stride 2	3×3 conv, stride 2	
Conv2d	112×112	3×3 Chromatic Layer, stride 1	3×3 conv, stride 1	
Conv2d	56×56	3×3 Chromatic Layer, stride 2	3×3 conv, stride 2	
Conv2d	56×56	3×3 Chromatic Layer, stride 1 $\times 2$	[3×3 conv, stride 1] $\times 2$	
Fusion	56×56	[ResOp, DeveilOp, SelfAttnOp, DecompOp, Depthwise-separable Conv, Dilated Conv, Skip]		
Fusion	28×28	[ResOp, DeveilOp, SelfAttnOp, DecompOp, Depthwise-separable Conv, Dilated Conv, Skip]		
Deconv2d	56×56	4×4 deconv, stride 2		
Conv2d	56×56	3×3 conv, stride 1		
Deconv2d	112×112	4×4 deconv, stride 2		
Conv2d	112×112	3×3 conv, stride 1		
Deconv2d	224×224	3×3 deconv, stride 2		
Conv2d (Output)	224×224	3×3 conv, stride 1		

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