Supplementary Material
All-in-one Image Restoration for Unknown Degradations Using Adaptive Discriminative Filters for Specific Degradations

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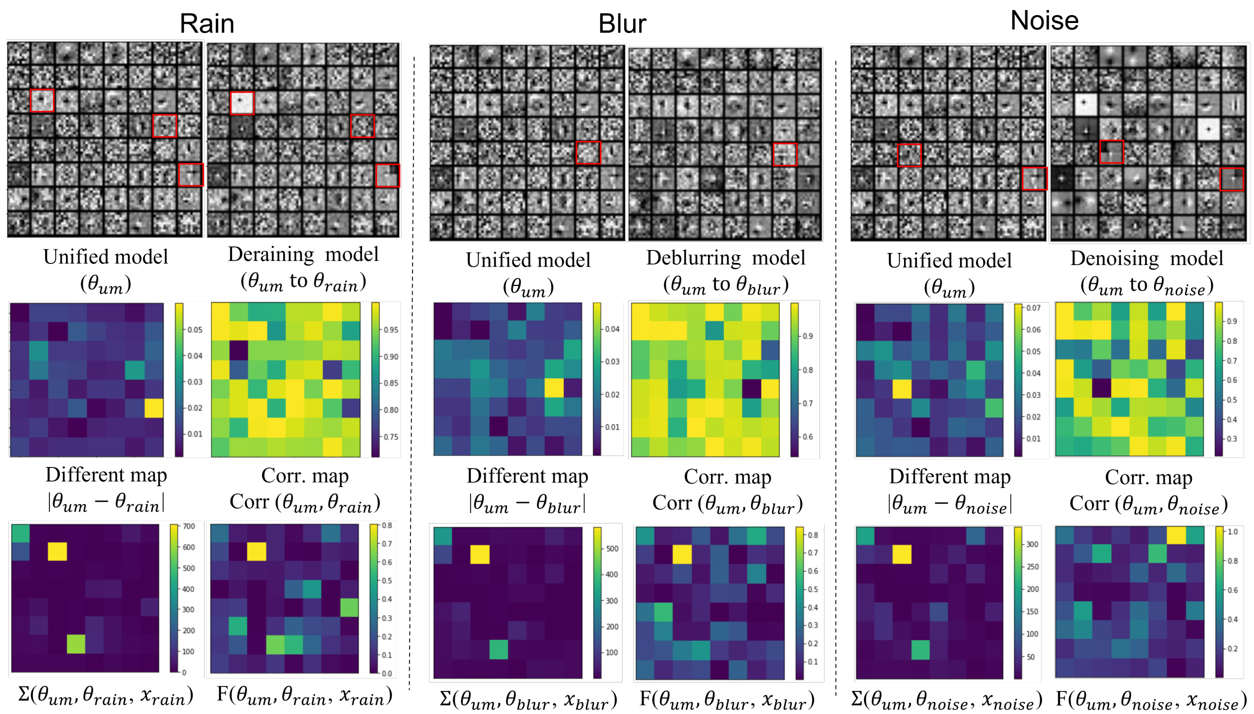

Figure 1. Visulaization of convolutional filters in UM for Rain-Noise-Blur and IM for Rain, Blur, Noise where IM was fine-tuned from UM with the difference, correlation map, $\sum$ map and FAIG-SD map (F) between them. $\sum(\theta_{um}, \theta_d, x)$ map is $\sum_{t=0}^{N-1} \mathcal{L}(\lambda(\alpha_t), x)/\lambda(\alpha_t)$, where $\lambda(\alpha) = \alpha\theta_{ab} + (1-\alpha)\theta_{ta}$. It was observed that the FAIG value differed depending on the task.

1. Kernel Analysis for Toy Experiment Using UM vs. IM

Figure 1 illustrates convolutional filters from the first layer of UM and IM for Rain-Noise-Blur task. The UM is shared for all cases and fine-tuned for Rain, Blur, and Noise tasks separately to generate IMs for each task. In all degradation cases, we consistently observed that only a small number of filters has changed by fine-tuning for a specific degradation from UM. We observed that $\sum$ map was similar, and also observed that the FAIG-SD map changed depending on the task.

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Table 1. Performance comparisons among different filter location selections for M in our CNN with ADS in LPIPS [7]: Random selection method (Ran), Encoder selection method (En), $|\theta - \hat{\theta}|$ selection method ($|\theta|$) and our FAIG-SD method (Ours) on Rain-Noise-Blur test dataset.

Added	Added 5% filters				Added 3% filters				Added 1% filters				Base
Task	Ran	En	$\|\theta\|$	**Ours**	Ran	En	$\|\theta\|$	**Ours**	Ran	En	$\|\theta\|$	**Ours**	UM
Rain	0.271	0.260	0.253	**0.230**	0.273	0.264	0.260	**0.234**	0.277	0.273	0.268	**0.246**	0.279
Noise	0.138	0.133	0.131	**0.128**	0.140	0.136	0.133	**0.130**	0.141	0.137	0.136	**0.133**	0.142
Blur	0.201	0.197	0.194	**0.191**	0.202	0.200	0.197	**0.193**	0.204	0.201	0.200	**0.199**	0.204
Avg.	0.203	0.196	0.193	**0.183**	0.205	0.200	0.197	**0.186**	0.207	0.204	0.201	**0.193**	0.208
Par.	33.0 M = 28.7M $\times$1.15				31.3 M = 28.7 M $\times$1.09				29.6 M = 28.7 M $\times$1.03				28.7

2. Experimental setups

Our experimental environment is the same as that of Chen *et al.* [2]. In order to discover the discriminative filter, we need to train a unified model and independent models for each task. All models were trained with 39,000 iterations and a warm-up strategy. The initial learning rate was 2×10^{-4} and the ADAM optimizer [4] with batch size of 32 was used to train. We used the cosine annealing learning rate decay technique with η_{min} equal to 1×10^{-6}. For fair comparison, the proposed method was evaluated on the same machine with NVIDIA A100 GPU using PyTorch [6]. The patch size was set to 224×224 and data augmentation for training such as random crop, horizontal flip, and 90-degree rotation were used. We adopt an architecture similar to MSBDN [3], just like Chen [2] and NAFNet [1] architectures, which has the state-of-the-art performance in IM based image restoration. We used the official codes of Airnet [5] and Chen [2] that were published by the original authors. we used an architecture similar to those of MSBDN, Chen, and NAFNet, which have state-of-the-art performance in IM-based image restoration was implemented in published code by the author. We conducted an experiment based on the MSBDN [3] network used by Chen [2] and NAFNet [1], which is the state-of-the-art result in IM-based image restoration.

3. More comparison studies for different mask selection in LPIPS

Table 1 summarizes the performance in LPIPS [7] and the number of parameters. Our method yielded substantially higher performance than other methods, demonstrating the effectiveness of selecting discriminative filters for each task in LPIPS [7] as well.

4. More Figures for Qualitative Results

Figures from 2 to 5 illustrate the qualitative results of the baseline methods and the prior arts (UM, Chen, AirNet) and our approach evaluated on the Rain-Noise-Blur and Rain-Snow-Haze. Compared to the prior arts, our proposed method consistently yielded visually well-restored images by alleviating the degradations.

References

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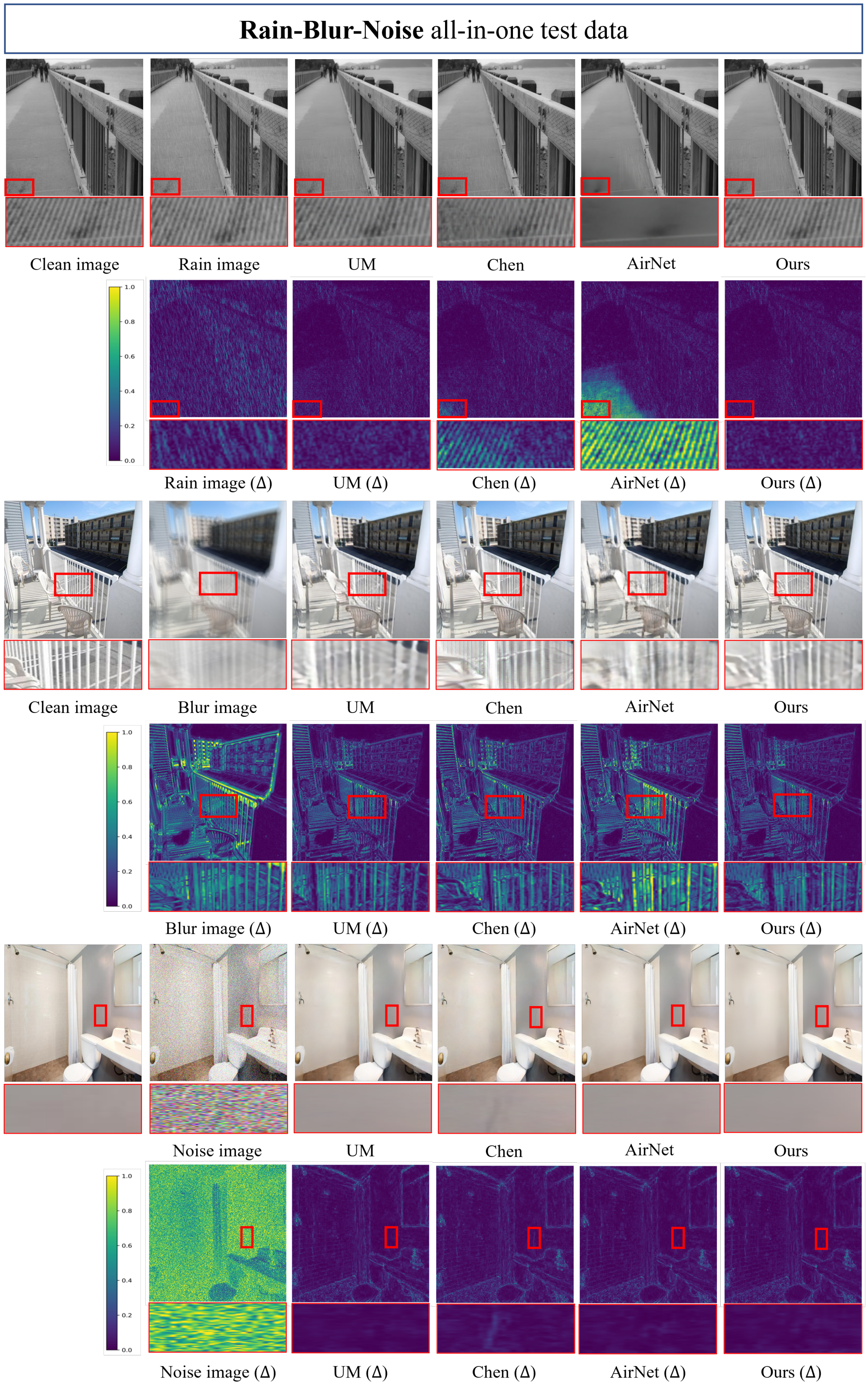

Figure 2. Qualitative results evaluated on the Rain-Blur-Noise test dataset for our proposed method, generic unified model(UM), Chen and AirNet. Our proposed method yielded visually excellent results for the multiple degradations.

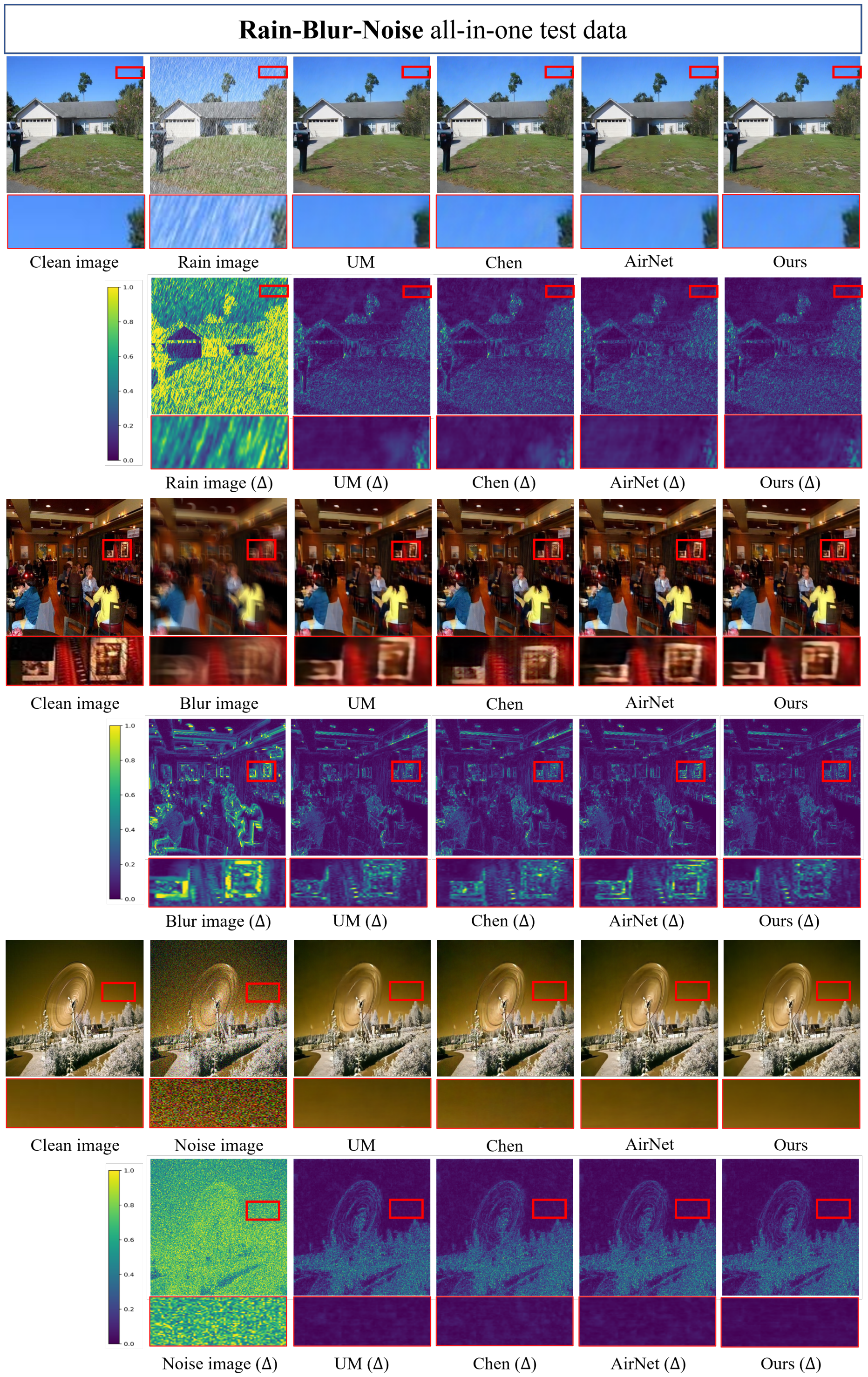

Figure 3. Qualitative results evaluated on the Rain-Blur-Noise test dataset for our proposed method, generic unified model(UM), Chen and AirNet. Our proposed method yielded visually excellent results for the multiple degradations.

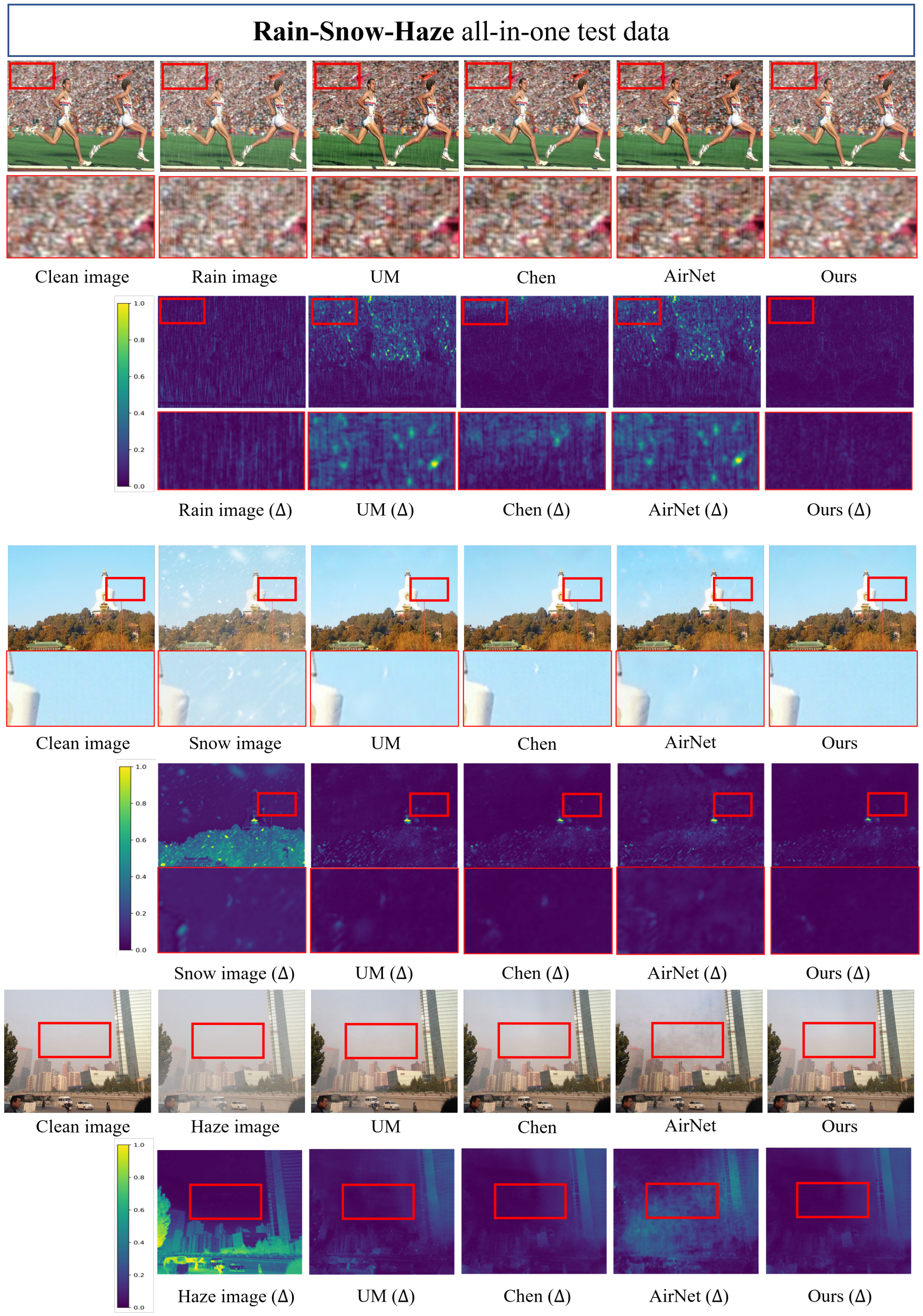

Figure 4. Qualitative results evaluated on the Rain-Snow-Haze test dataset for our proposed method, generic unified model(UM), Chen and AirNet. Our proposed method yielded visually excellent results for the multiple degradations.

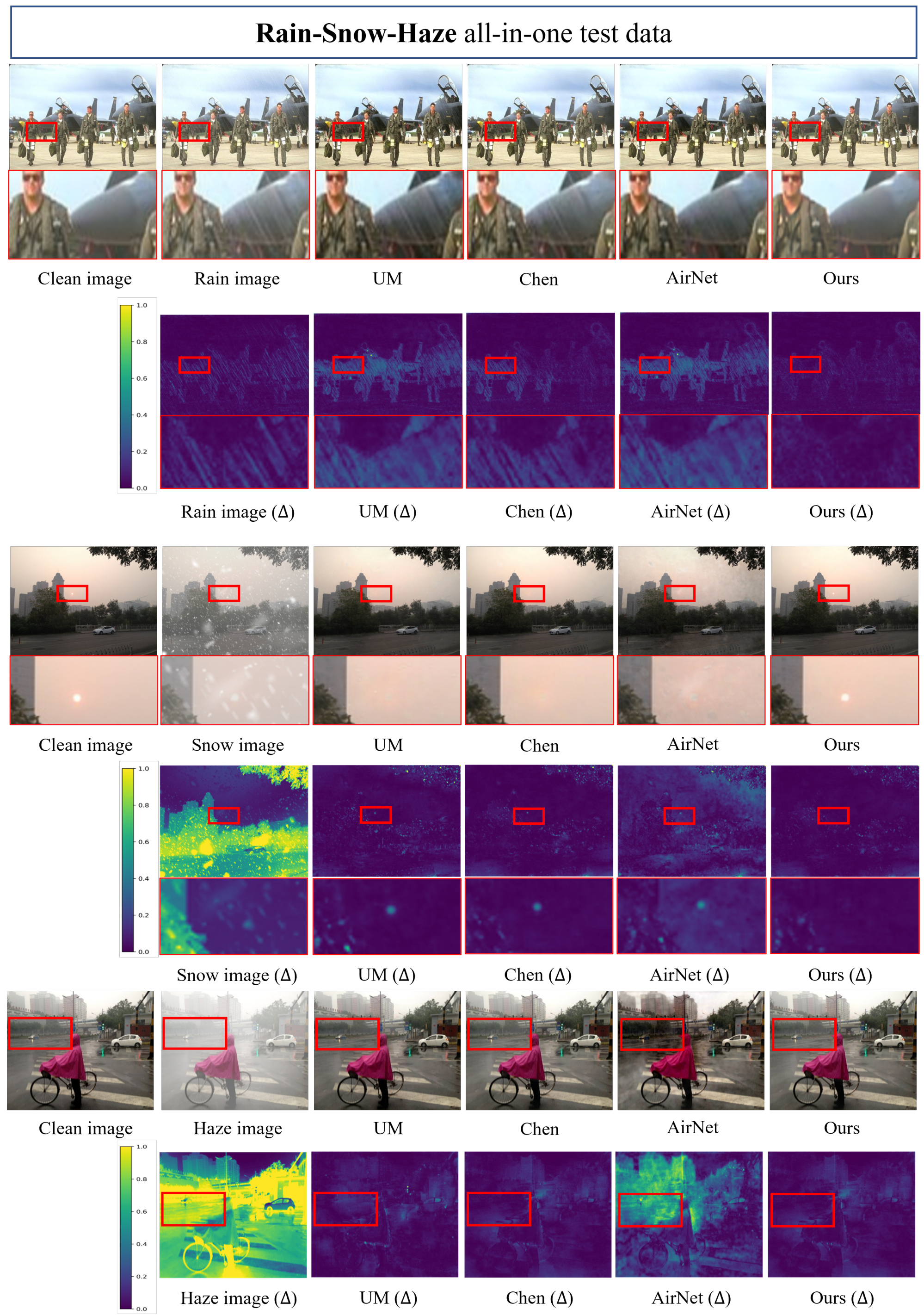

Figure 5. Qualitative results evaluated on the Rain-Snow-Haze test dataset for our proposed method, generic unified model(UM), Chen and AirNet. Our proposed method yielded visually excellent results for the multiple degradations.