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

Dongwon Park[1,4]. **Byung Hyun Lee**[2] , **Se Young Chun** [1,2,3]

[1] INMC, [2] Dept. of ECE, [3] IPAI, Seoul National University, Republic of Korea,

[4] Dept. of EE, UNIST, Republic of Korea

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Problem : Image restoration for multiple degradations

- Image restoration for real-world environments is a challenging problem since it must deal with **unknown multiple degradations.**


Noise


Rain


Blur

…

Degradation images

Degradation occurs due to unknown influences

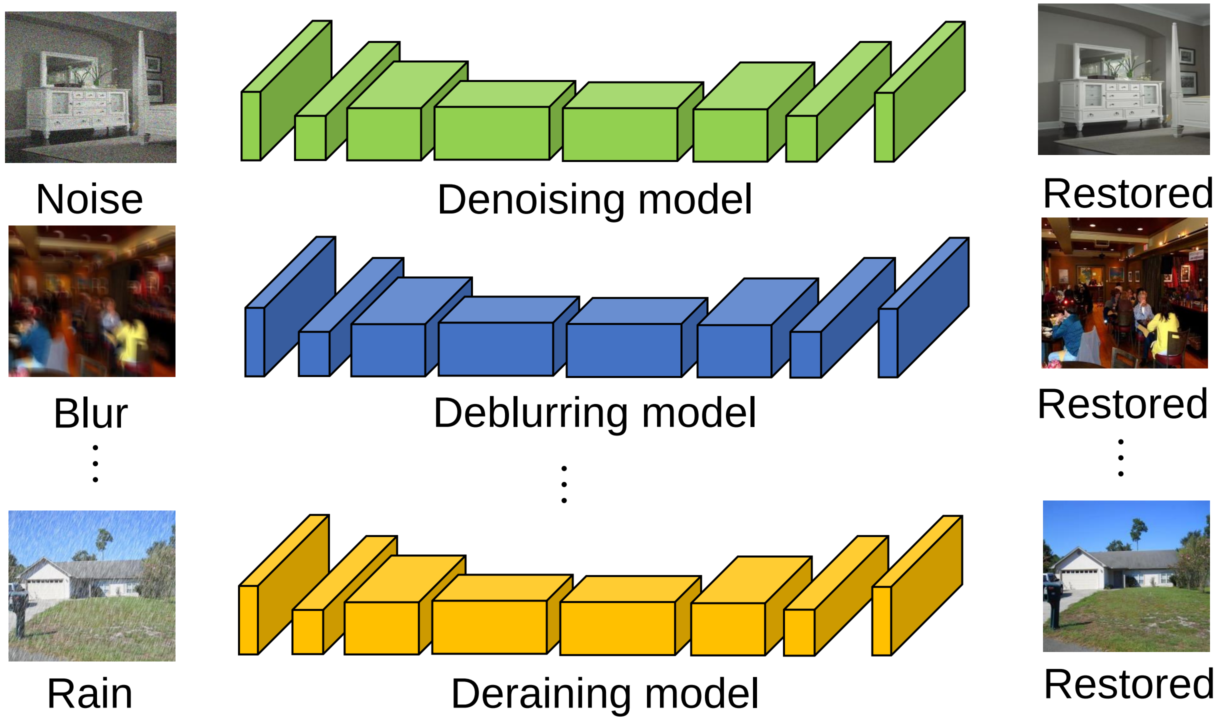
Image restoration for **unknown multiple degradations**

…

Restored images

Related works : Independent modes (IM)

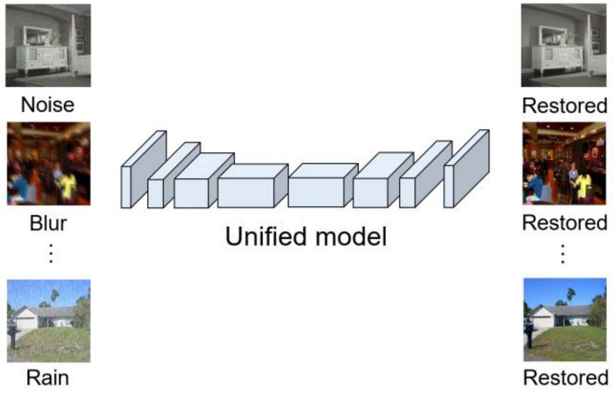
- To handle known multiple degradations is to develop a single network architecture and train it with different degradation datasets to generate independent modes (IM) for various degradations.



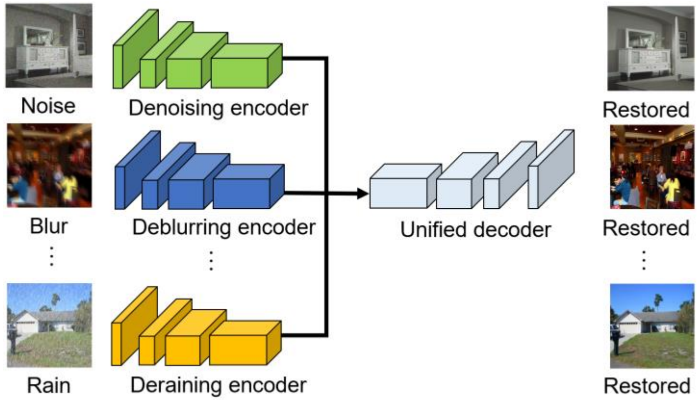
Promising results but require **large network** and/or **heavy computation.**

S. W. Zamir, et al. "Multi-stage progressive image restoration," in CVPR, 2021.
S. W. Zamir, et al. "Restormer: Efficient transformer for high-resolution image restoration," in CVPR, 2022.
C. Mou, et al. "Deep generalized unfolding networks for image restoration," in CVPR, 2022.
L. Chen, et al. "Simple baselines for image restoration," ECCV, 2022.
X. Chu, et al. "Improving image restoration by revisiting global information aggregation," ECCV, 2022.

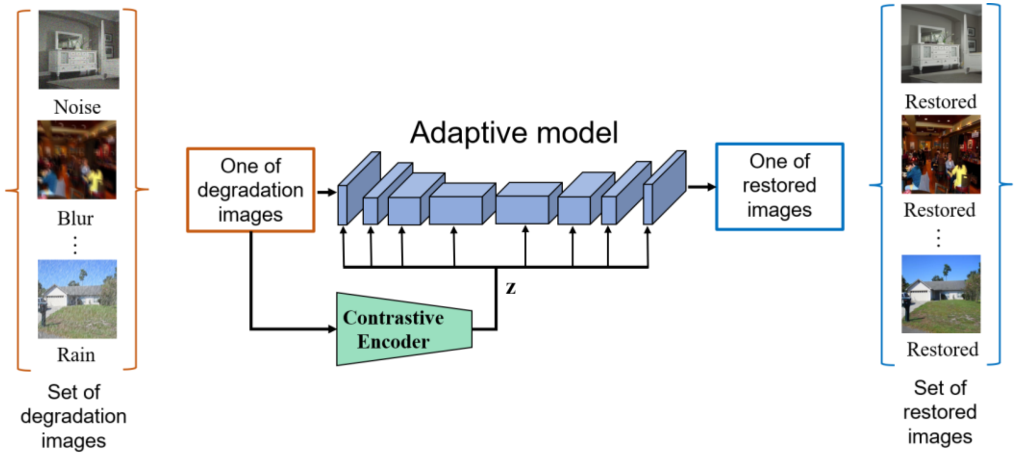
Related works : All-in-one image restoration for multiple degradations



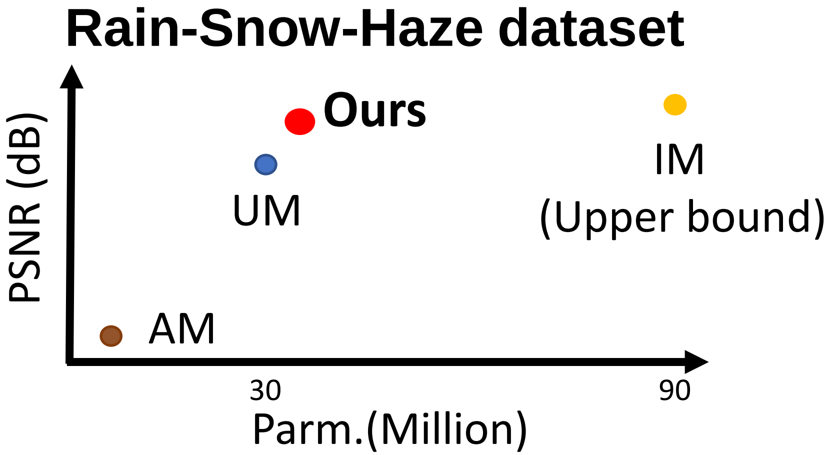
(a) Unified Model (**UM**)



(b) Model with independent Encoders (**ME**)



(c) Adaptive Model (**AM**)



(d) Number of parameters (Million) vs. PSNR (dB)

W. Chen, et al. “Learning multiple adverse weather removal via two-stage knowledge learning and multicontrastive regularization: Toward a unified model,” in CVPR, 2022

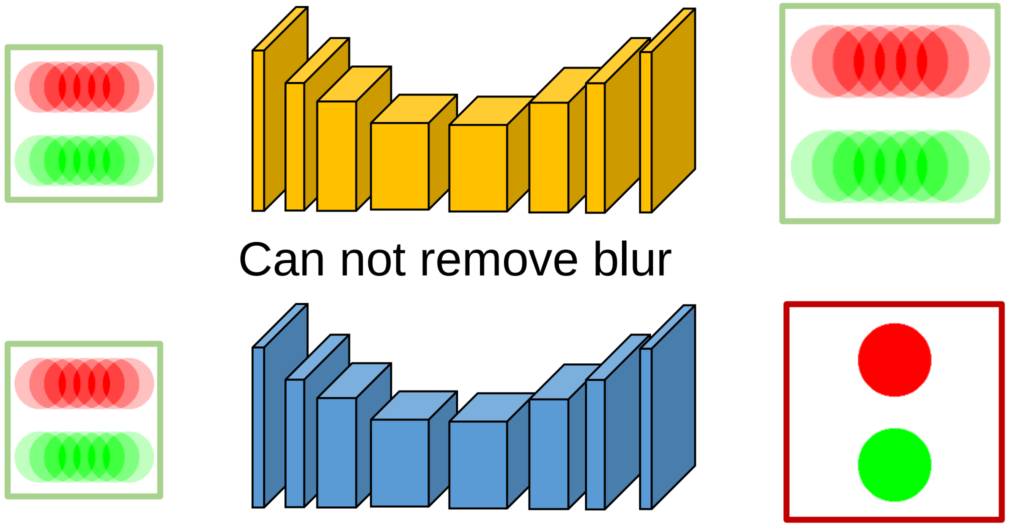
B. Xiao, etal. “All-in-one image restoration for unknown corruption,” in CVPR, 2022. , R. Li, et al. “All in one bad weather removal using architectural search,” in CVPR, 2021

Related works : Filter attribution integrated gradients (FAIG)

- L. Xie et al. proposed **FAIG** that can identify **discriminative filters** of specific degradation.

Baseline model (θ_{ab})

Target model (θ_{ta})



Can not remove blur

Can remove blur

The **baseline network (θ_{ab})** is a pure SR network that **cannot remove any degradations.**

The **target network** (θ_{ta}) is a re-trained network that can deal with **complex degradations**

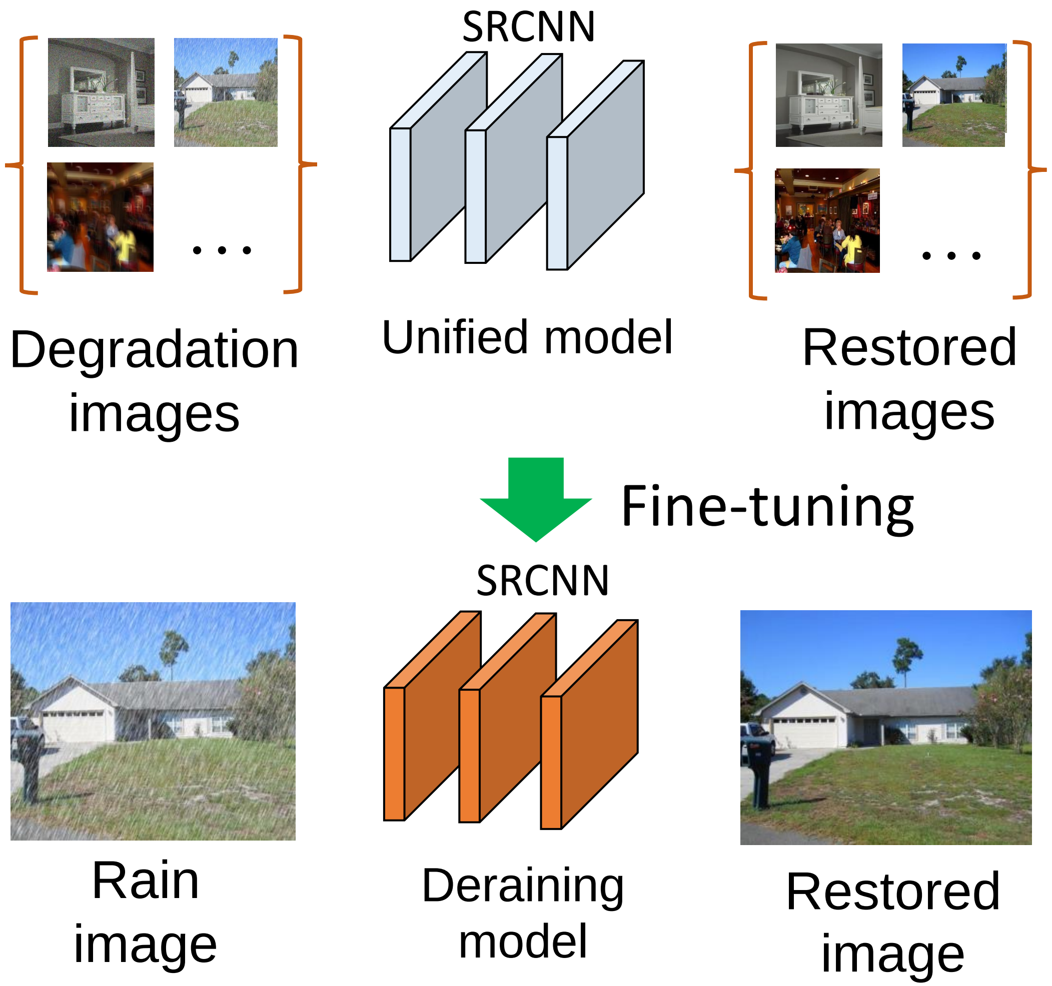
FAIG accumulate gradients along a straight-line path. i denote the index of the network kernel.

$$\lambda(\alpha) = \alpha\theta_{ab} + (1-\alpha)\theta_{ta}$$

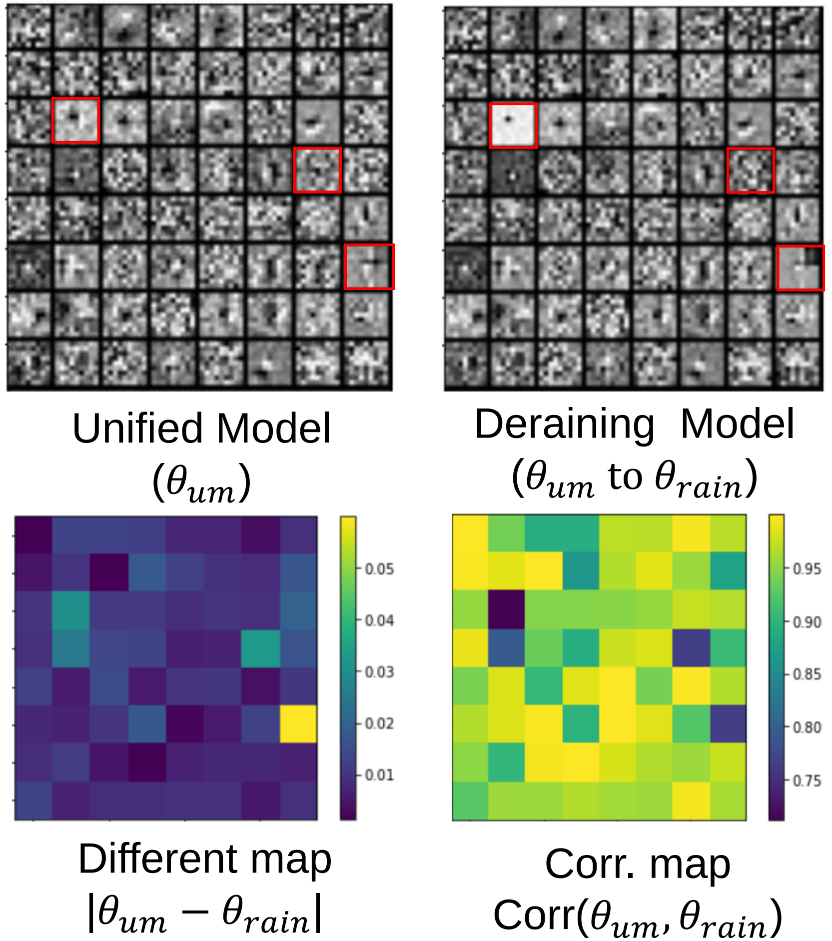
$$\text{FAIG:} \quad \mathrm{F}_i(\theta_{ta}, \theta_{ab}, x) \approx \left| \frac{1}{N}[\theta_{ta} - \theta_{ab}]_i \sum_{t=0}^{N-1} \left[\frac{\partial \mathcal{L}(\lambda(\alpha_t), x)}{\partial \lambda(\alpha_t)} \right]_i \right|$$

FAIG : L. Xie, et al. “Finding discriminative filters for specific degradations in blind super-resolution,” NIPS, 2021

Motivation : UM and IM differ only in a few network kernels.



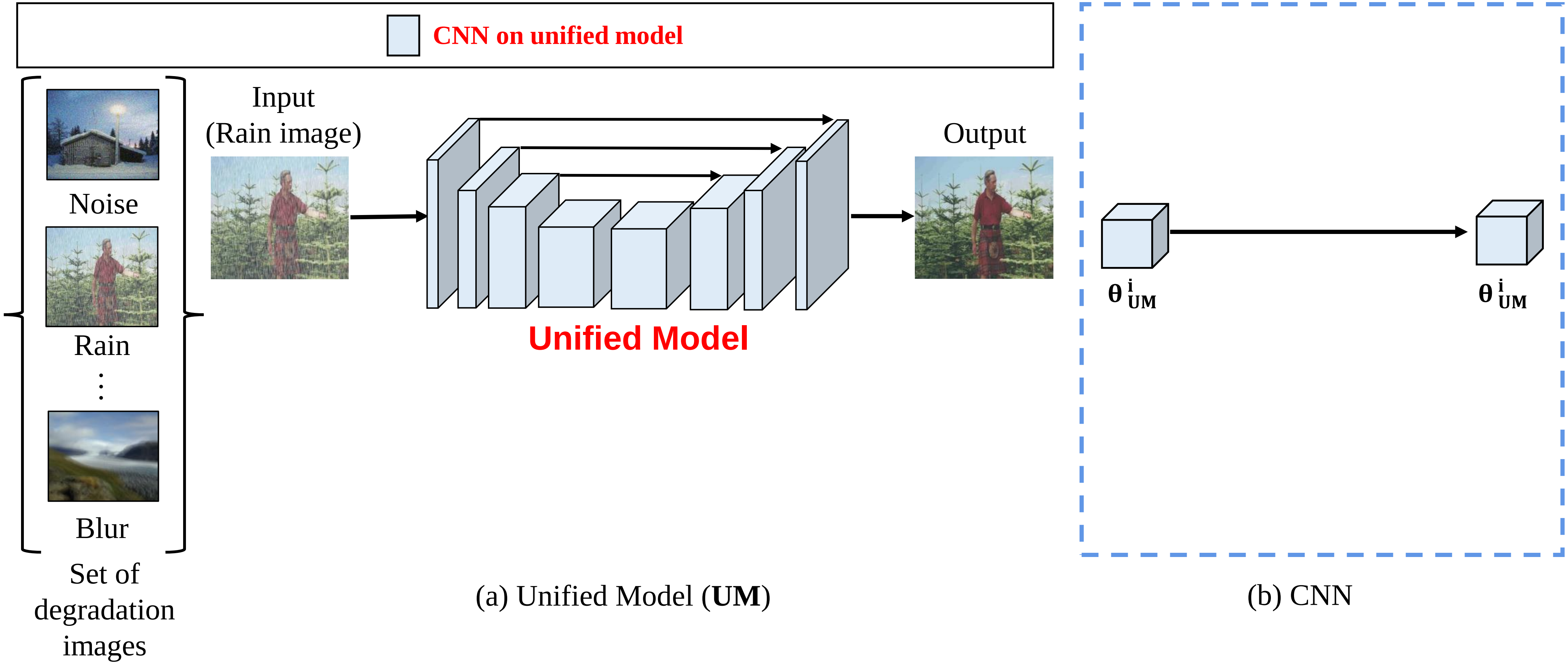
Visualization of the **first convolutional filter** of SRCNN



C. Dong, et al. "Image super-resolution using deep convolutional networks," IEEE TPAMI, 2015.

Method : Step 1 - Unified model

- First, we train a unified model for all degradations.

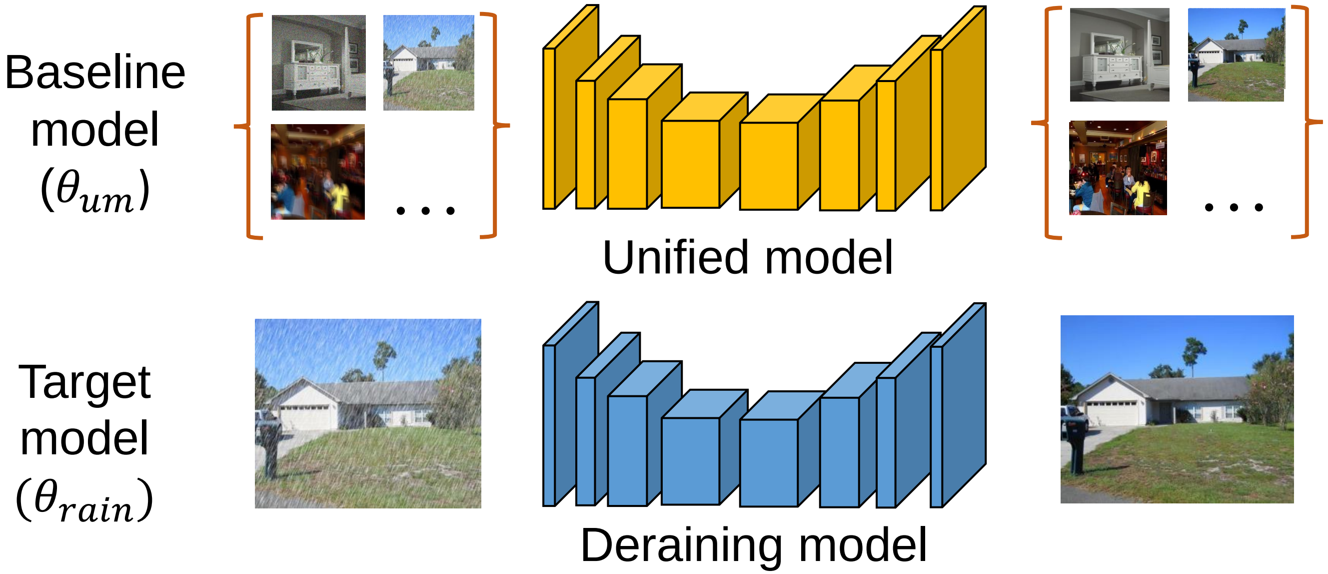


(a) Unified Model (**UM**)

(b) CNN

Method : Step 2 - FAIG for multiple degradations

- We leveraged the FAIG [57] in (5) to locate discriminative filters for **specific degradation.**



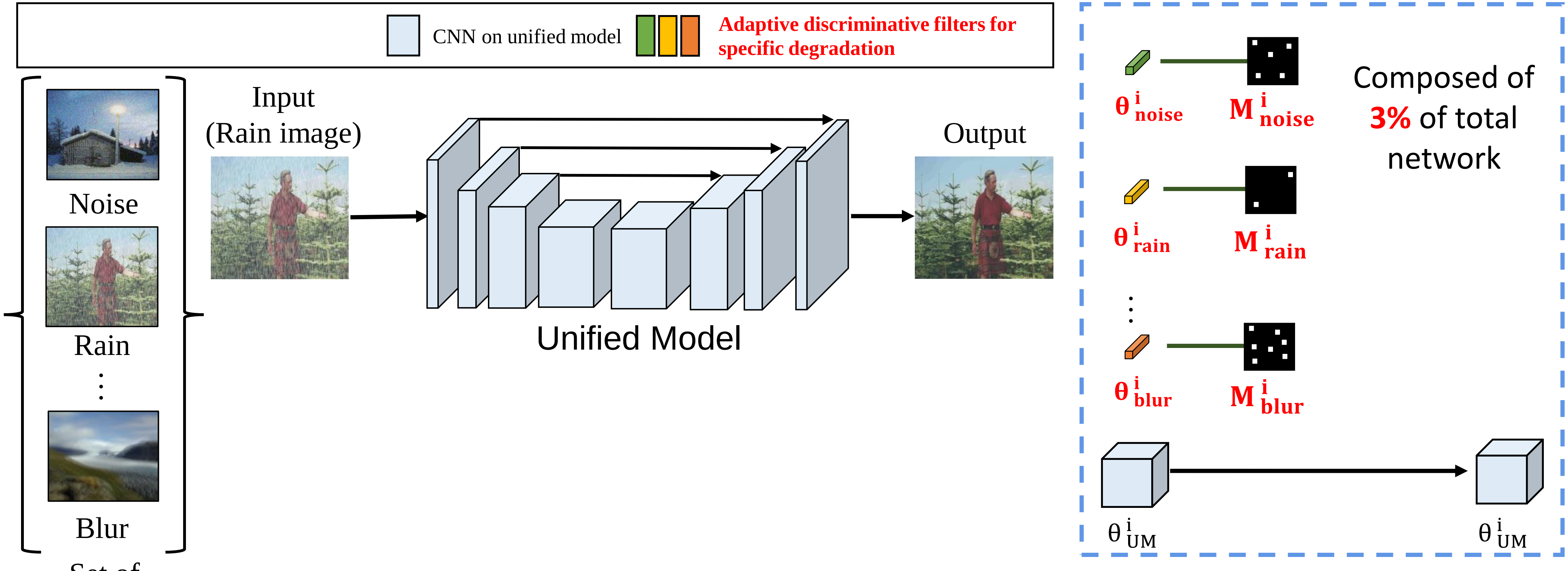
The **baseline network ($\boldsymbol{\theta_{um}}$)** is the unified model trained for all degradations.

The **target network** ($\boldsymbol{\theta_d}$) for the **specific degradation (d)** is constructed by fine-tuning the **baseline network ($\boldsymbol{\theta_{um}}$).**

- We create k target models and compute FAIG $F_i(\theta_d, \theta_{um}, x)$ for each degradation $d = 1, \dots, k$ and all kernels i.
- For each d, the kernels of top q% FAIG scores are selected where q ranges from 1 to 5.
- Selected kernel indices are used to generate masks (M_d) with 1 for selected kernels and 0 otherwise

Method: Step 2 - Constructing FAIG for multiple degradations

- Second, we leveraged the **FAIG** to locate discriminative filter mask (**M_d**) for multiple degradations.
- The ratio of the mask (**M_d**) was set to **3%** for each task through comparison studies.

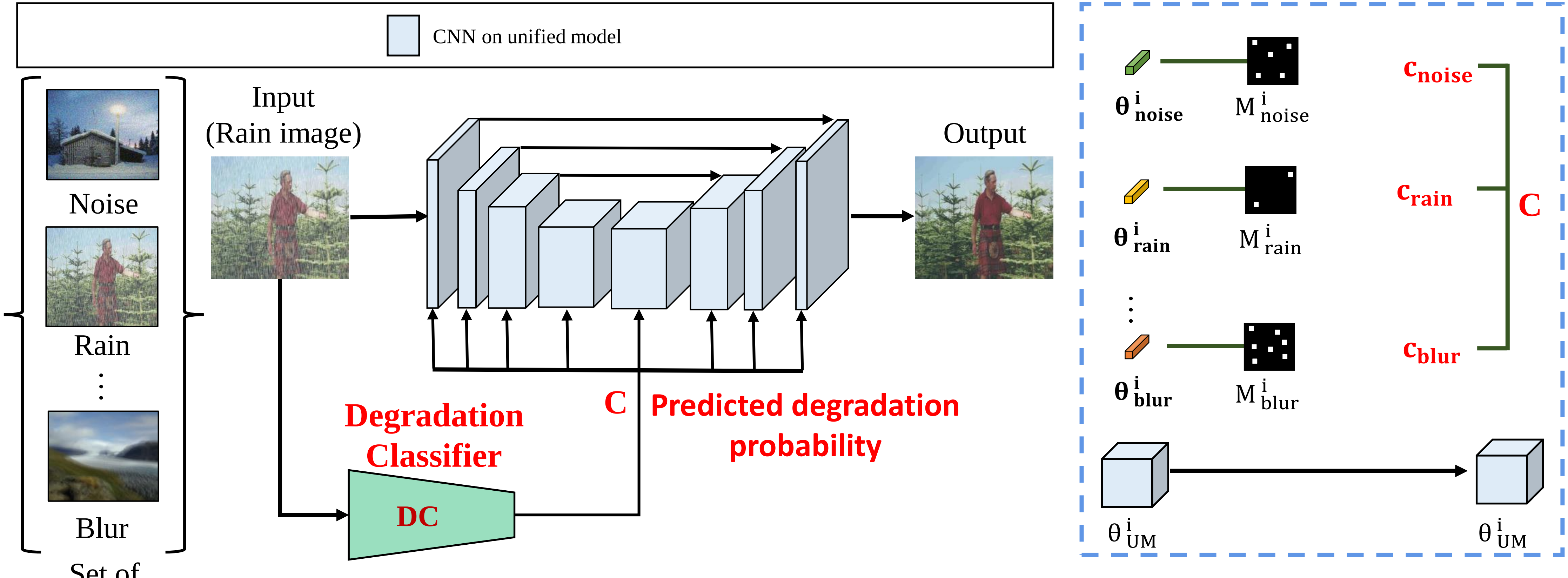


(a) Unified Model (**UM**)

(b) CNN with **discriminative filter masks**

Method : Step 3 - Degradation classifier

- Third, the degradation classifier (**DC**) aims to **classify the degradation** type from the input image.
- We propose a degradation classifier (**DC**) to adaptively **change the network parameters in the CNN with ADS**

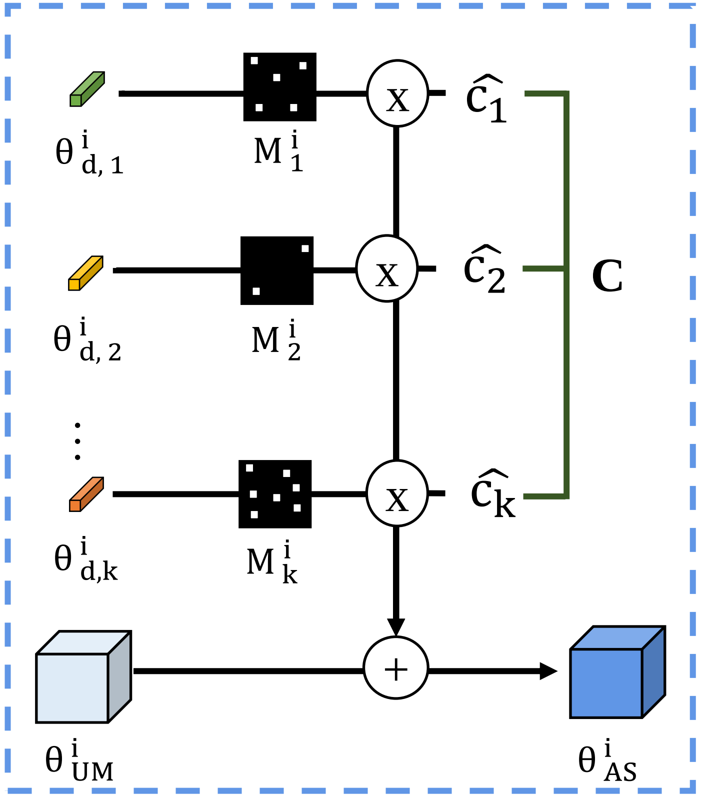


(a) Unified Model (UM) and Degradation Classifier (DC)

(b) CNN with discriminative filter indexes

Method: Step 4 - CNN with adaptive discriminative filters

- CNN with Adaptive Discriminative filters for Specific degradation (CNN-ADS)



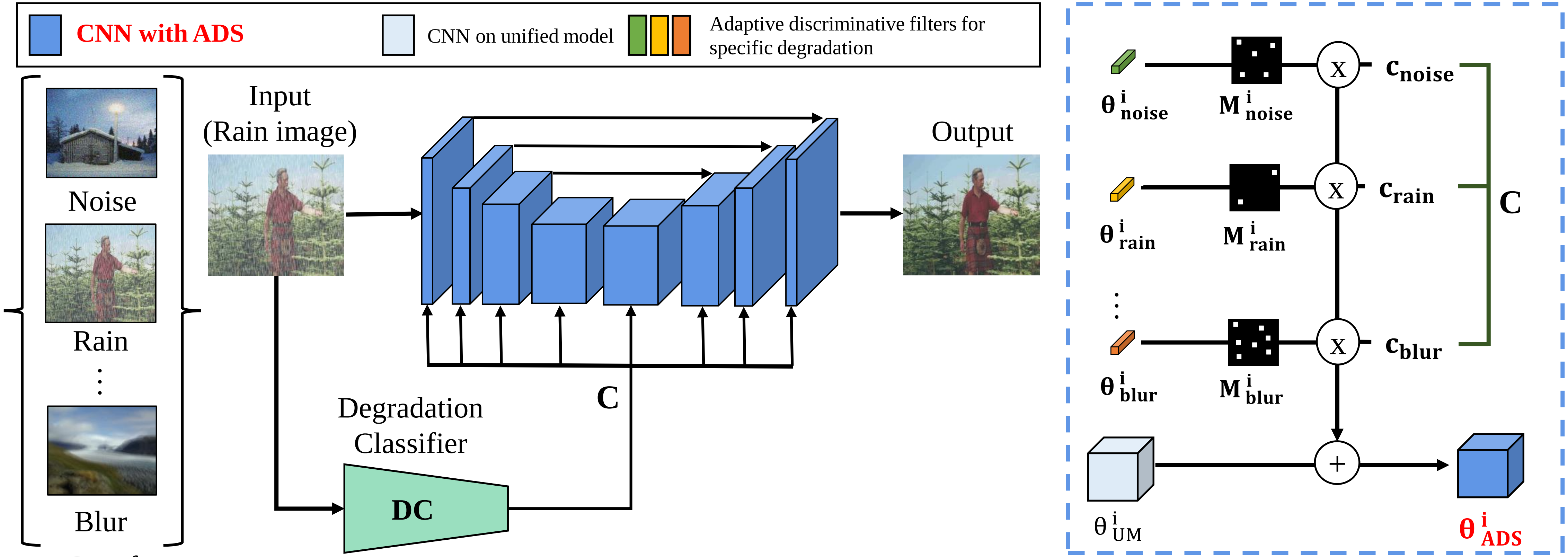
- Our proposed CNN-ADS is defined as follows:

$$\theta^i_{ads} = \theta^i_{um} + \sum_{d=1}^{k} \hat{c}_d \, \theta^i_d * M^i_d$$

- θ_{um} is a unified model
- θ_{d} is an additional kernel for specific degradation.
- $\hat{c}_{d}$ is the predicted degradation type.
- M_d is a mask for filters in the network such that 1 is assigned only to the filter indices whose FAIG-SD values are the top q% scores for a degradation type d.

Method: Step 4 - CNN with adaptive discriminative filters

- We propose a **CNN with ADS** (Adaptive Discriminative filters for Specific degradation), implemented by the masks **(M_d)** that are constructed using our FAIG-SD and the predicted degradation probability **(C)** as illustrated.



(a) Adaptive discriminative filter-based Models for Specific degradation (ADMS) and Degradation Classifier (DC)

(b) CNN with Adaptive Discriminative filters for Specific degradation **(CNN-ADS)**

Experiments dataset

Rain-Blur-Noise dataset (Different characteristics)

- The noise image physical model:

$$x_{\text{noise}} = x^{\text{gt}} + \epsilon, \quad \epsilon \sim \mathcal{N}(0, \sigma_\epsilon^2 I)$$

- The blur image physical model:

$$x_{\text{blur}} = x^{\text{gt}} * k$$

- The rain image physical model:

$$x_{\text{rain}} = T \odot (x^{\text{gt}} + S) + (1 - T) \odot A$$

Rain-Snow-Haze dataset (Similar characteristics)

- We evaluated our proposed method with the Rain-Snow-Haze datasets similar to the environment of W. T. Chen, et al.

$$x_{\text{rain,snow,haze}} = T \odot (x^{\text{gt}} + S) + (1 - T) \odot A$$

W. T. Chen, et al. "Learning multiple adverse weather removal via two-stage knowledge learning and multi-contrastive regularization: Toward a unified model," in CVPR, 2022

Comparison studies for selected filter locations

Performance comparisons among different filter location selection for M in **our CNN with AS** : Random selection method (Ran), Encoder selection method (En), $|\theta_{\mathrm{um}} - \theta_{\mathrm{d}}|$ selection method ($|\theta|$) and **our proposed FAIG-SD method (Ours)** on Rain-Noise-Blur 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	32.23	32.45	32.60	**32.80**	32.19	32.44	32.52	**32.74**	32.15	32.35	32.37	**32.56**	32.12
Blur	26.81	26.85	27.22	**27.70**	26.74	26.85	27.06	**27.57**	26.65	26.77	26.85	**27.28**	26.61
Noise	31.04	31.25	31.32	**31.46**	31.01	31.24	31.26	**31.42**	30.98	31.17	31.14	**31.30**	30.97
Avg.	30.03	30.18	30.38	**30.65**	29.98	30.17	30.28	**30.58**	29.93	30.10	30.12	**30.38**	29.90
Par.	33.0 M = 28.7M ×1.15				31.3 M = 28.7 M ×1.09				29.6 M = 28.7 M ×1.03				28.7

Comparisons among all-in-one on Rain-Blur-Noise

Quantitative performance comparison (Airnet and Chen) on Rain-Blur-Noise test dataset in PSNR (dB), parameter size (Par in Million). MSBDN-Large (M-L) has increased number of network parameters by 5.9 M.

Network	M	Rain	Blur	Noise	Avg.	Par.
NAFNet	IM	33.03	30.30	31.59	31.64	**51.3**
MSBDN	IM	33.02	28.79	31.52	31.11	**83.1**
NAFNet	UM	32.99	29.46	31.39	31.28	17.1
MSBDN	UM	32.12	26.61	30.97	29.90	28.7
MSBDN-L	UM	32.25	26.81	31.00	30.02	34.6
MSB-Chen		32.14	25.91	30.85	29.63	28.7
Airnet		32.49	26.84	31.41	29.13	7.6
NAFNet	**Ours**	**33.15**	**29.99**	**31.53**	**31.56**	18.9
MSBDN	**Ours**	**32.74**	**27.56**	**31.42**	**30.58**	31.6

W. T. Chen, et al. "Learning multiple adverse weather removal via two-stage knowledge learning and multi-contrastive regularization: Toward a unified model," in CVPR, 2022
B. Li et al. "All-in-one image restoration for unknown corruption," in CVPR, 2022

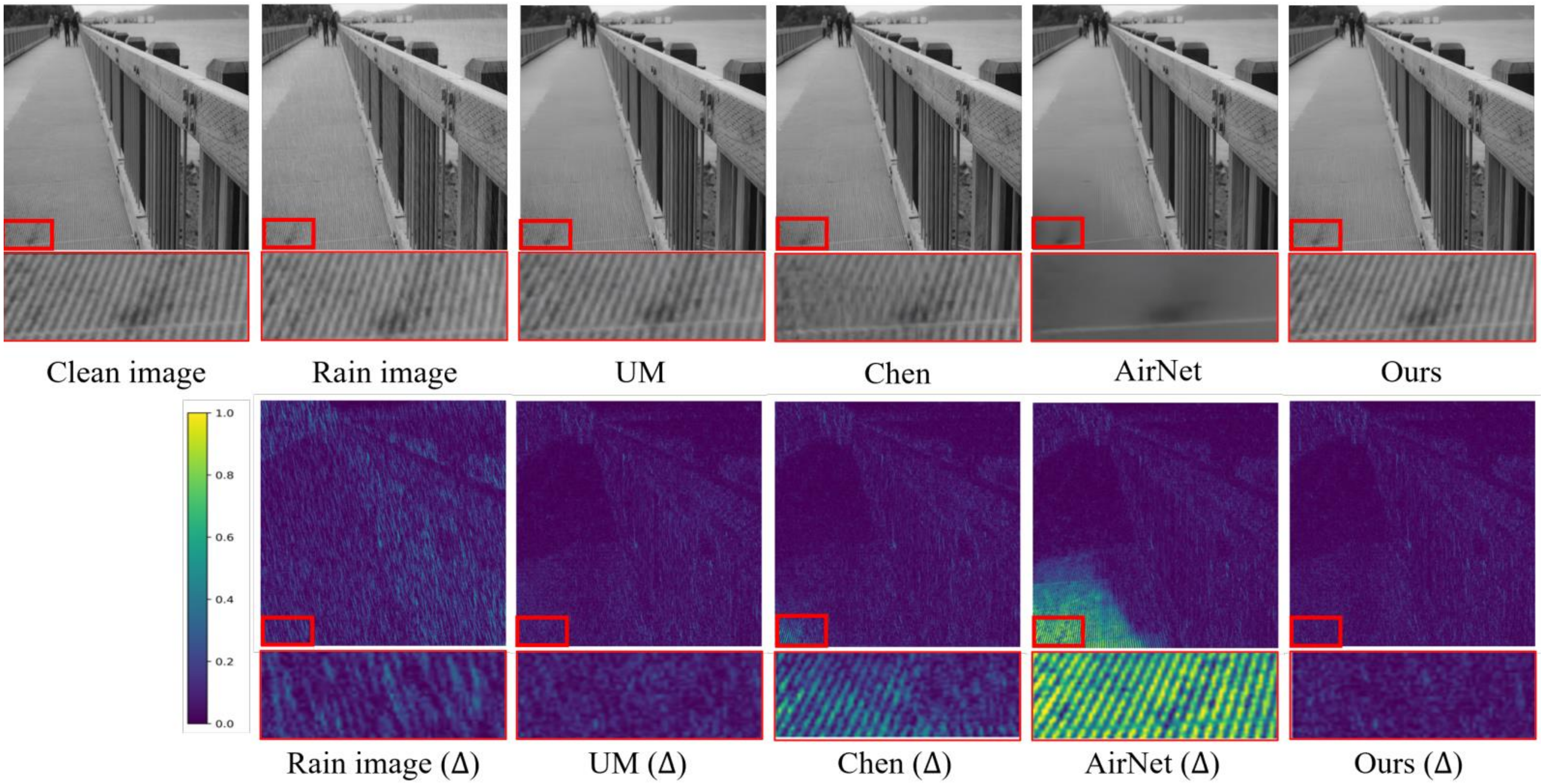
Comparisons among all-in-one on Rain-Snow-Hazy

Quantitative performance comparison (Airnet and Chen) on the Rain-Snow-Hazy test dataset in PSNR (dB), parameter size (Param in Million). “Chen, Ours” is a method to combine ours with Chen.

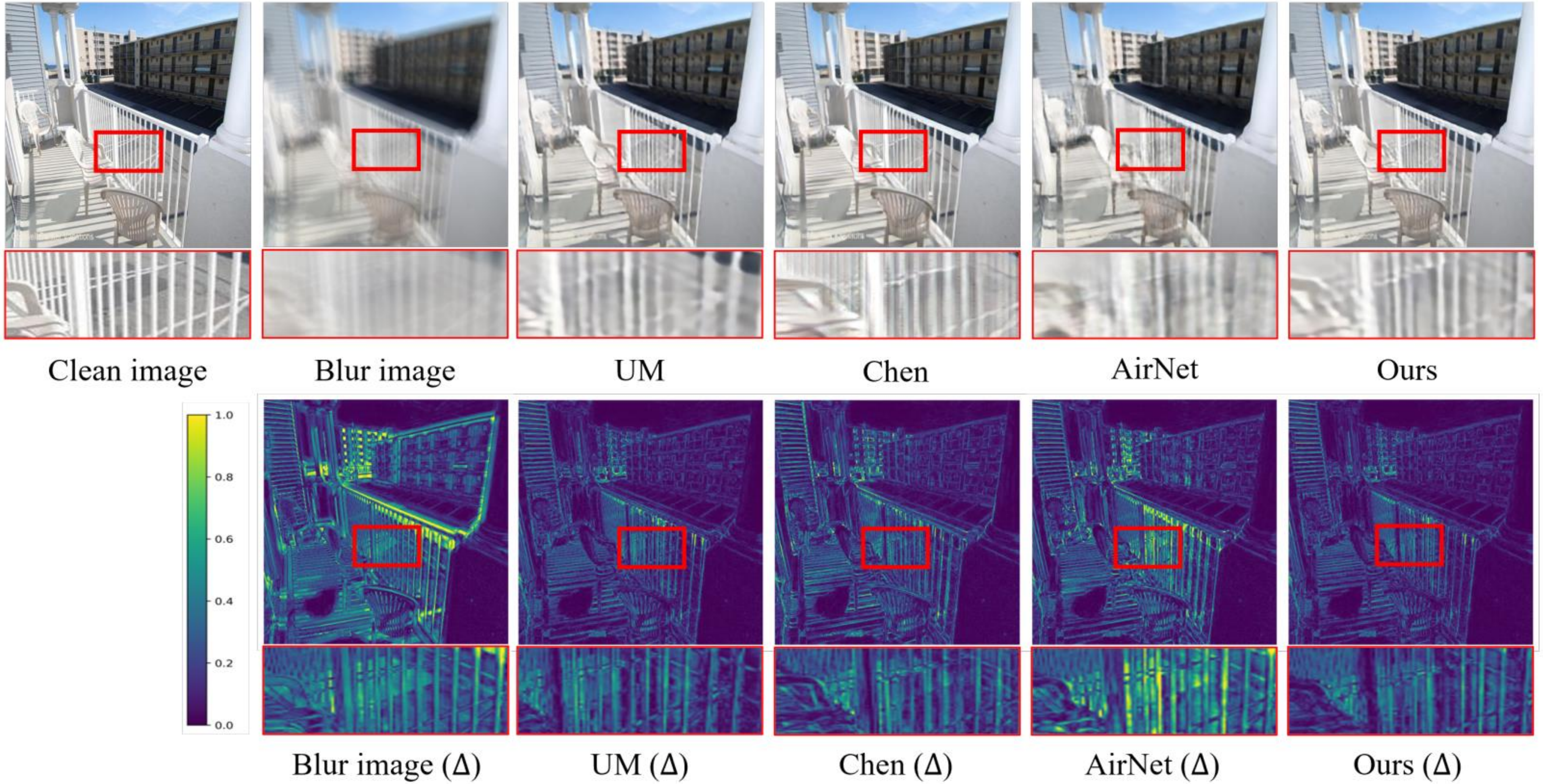
Network	M	Rain	Blur	Noise	Avg.	Par.
MSBDN	IM	34.81	31.42	31.67	32.63	86.1
MSBDN	UM	30.77	30.56	30.45	30.59	28.7
MSBDN-Chen		31.52	32.28	30.54	31.45	28.7
Airnet		30.08	26.91	26.11	27.70	7.6
MSBDN	Ours	**32.07**	32.41	30.38	31.62	31.6
MSBDN	Chen, Ours	31.89	**33.83**	**30.56**	**32.09**	31.6

W. T. Chen, et al. “Learning multiple adverse weather removal via two-stage knowledge learning and multi-contrastive regularization: Toward a unified model,” in CVPR, 2022
B. Li et al. “All-in-one image restoration for unknown corruption,” in CVPR, 2022

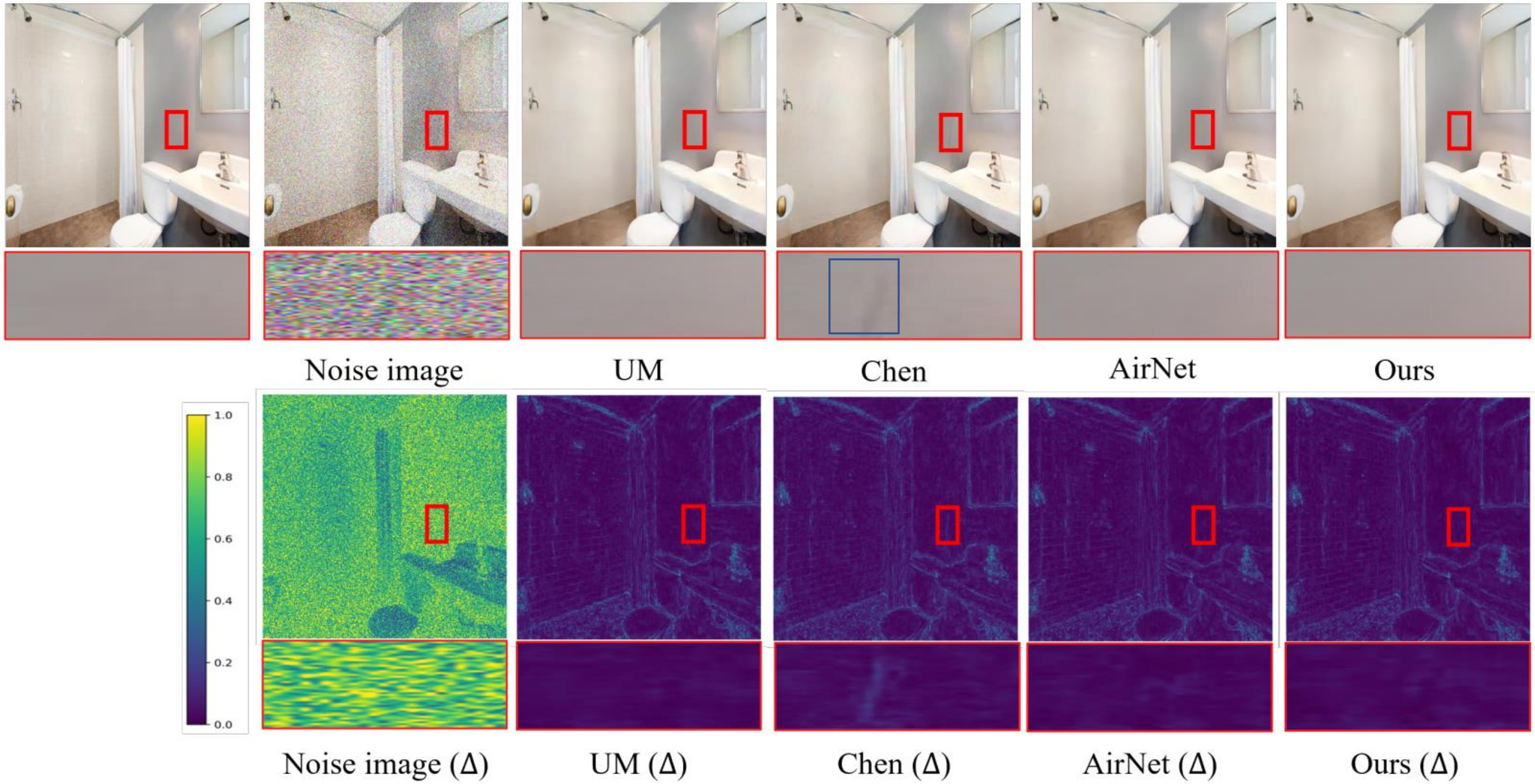
Comparisons among all-in-one on Rain-Blur-Noise



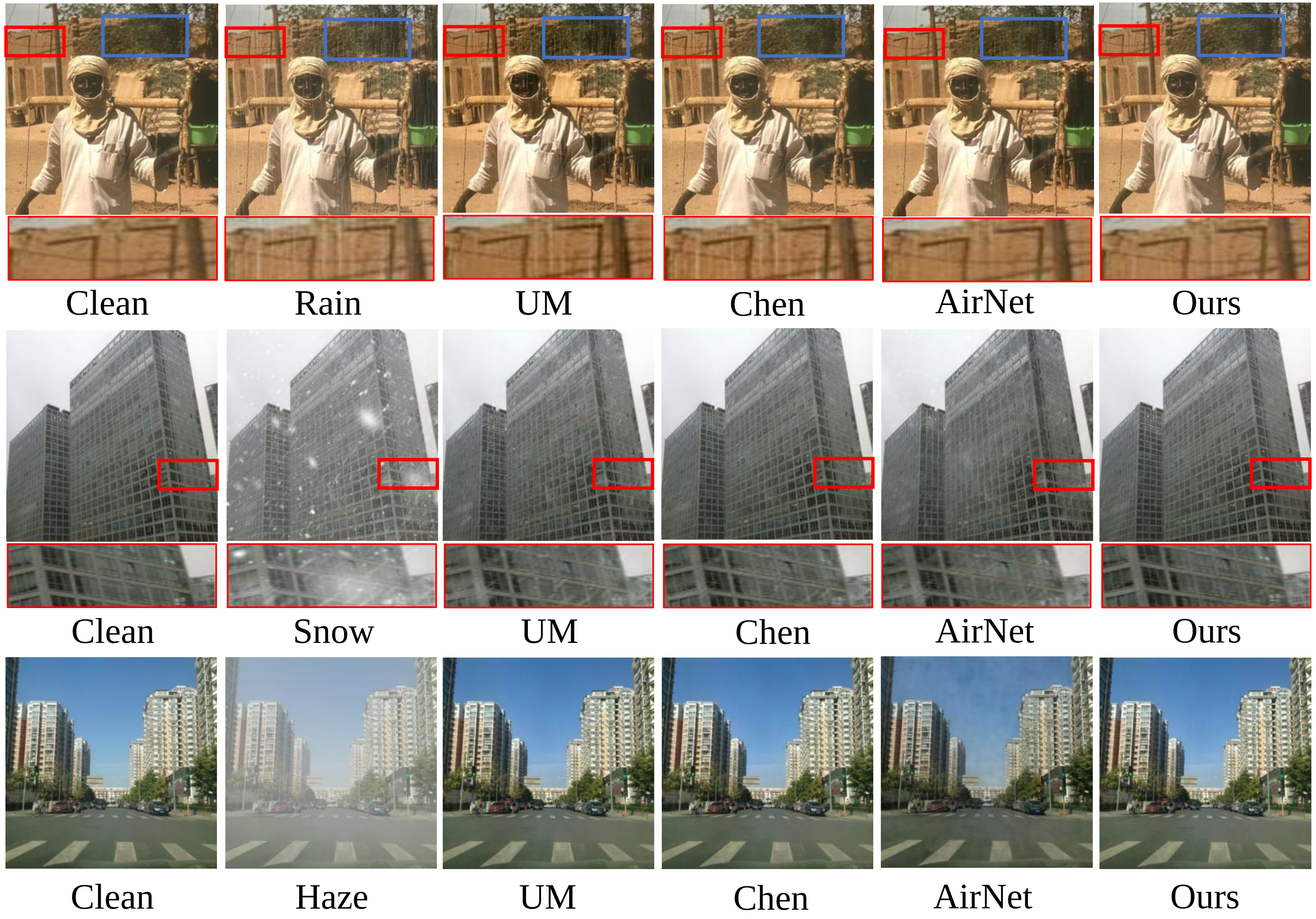
Comparisons among all-in-one on Rain-Blur-Noise



Comparisons among all-in-one on Rain-Blur-Noise

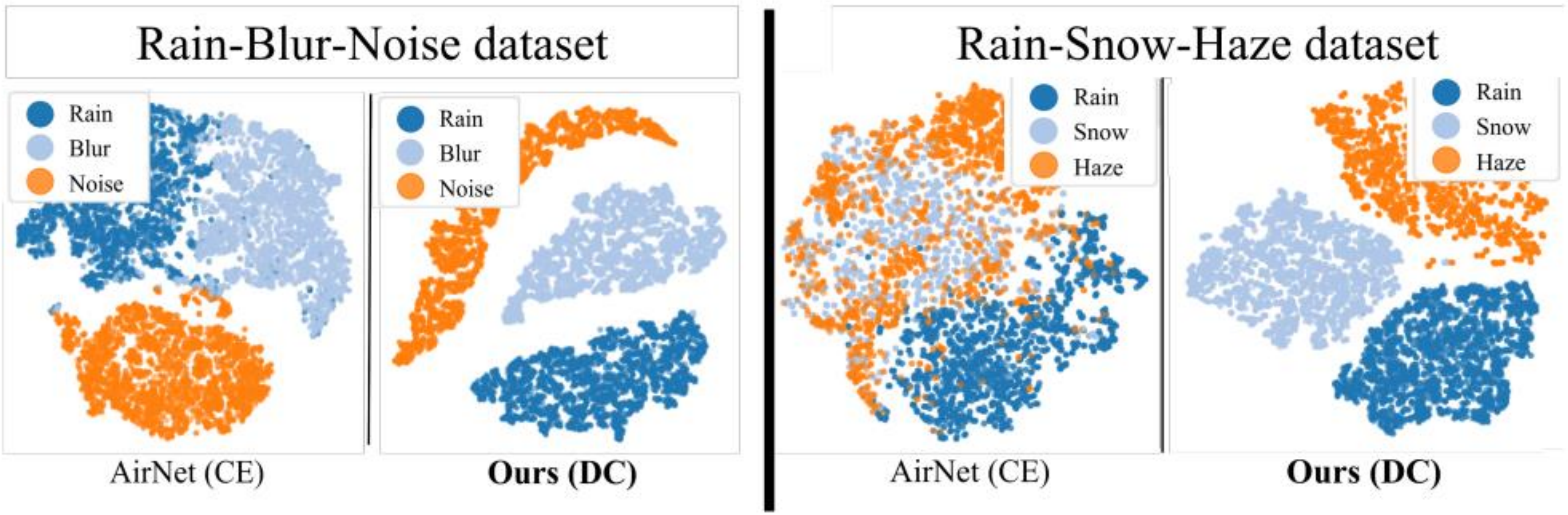


Comparisons among all-in-one on Rain-Snow-Hazy



Visualization of representations

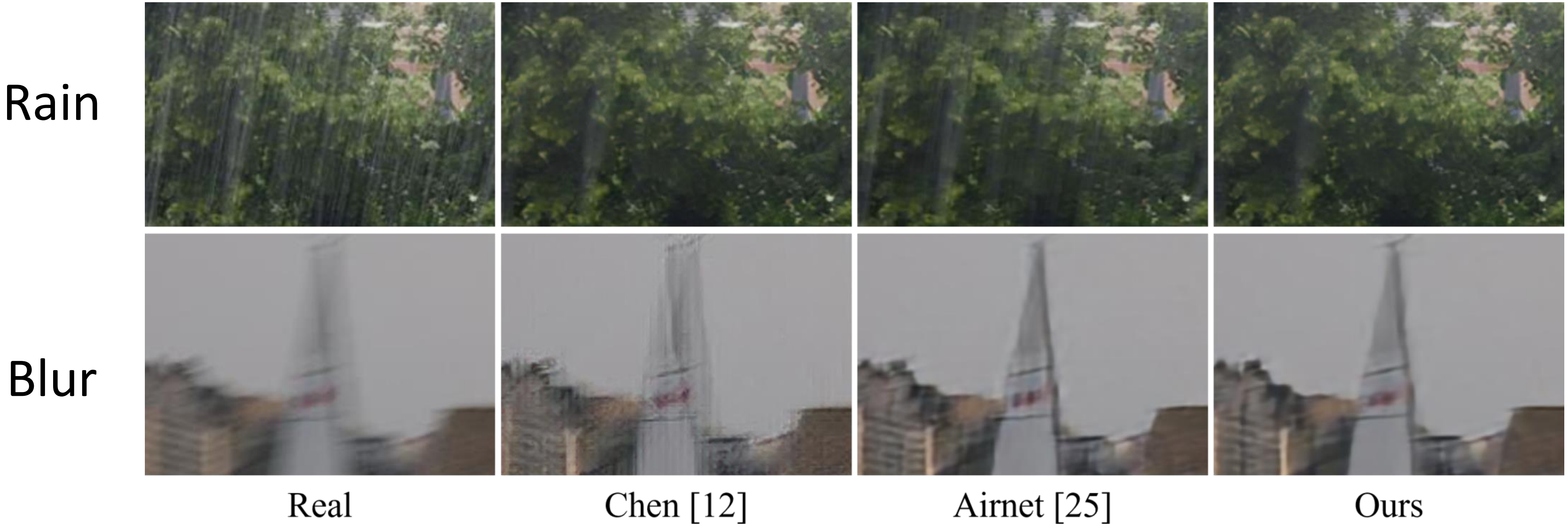
Visualization of representations for degradation types such as similar combinations of degradation, Rain-Blur-Noise and different combination of degradation, Rain-Snow-Haze.



B. Li et al. "All-in-one image restoration for unknown corruption," in CVPR, 2022

Comparisons among all-in-one on Real Rain and Blur

Qualitative results evaluated on the real rain (top) and real blur (bottom) for Ours (well on both), Chen [12] (well on one) and AirNet [26] (well on the other) trained on synthetic data.



W. T. Chen, et al. "Learning multiple adverse weather removal via two-stage knowledge learning and multi-contrastive regularization: Toward a unified model," in CVPR, 2022
B. Li et al. "All-in-one image restoration for unknown corruption," in CVPR, 2022

Summary

☐We proposed all-in-one image restoration method for unknown multiple degradations with adaptive discriminant filters for specific degradations using our FAIG-SD and degradation classifier.

☐Our proposed method with explicit parameter disentanglement for multiple degradations outperform state-of-the-art all-in-one image restoration methods on both Rain-Snow-Haze and Rain-Noise-Blur.

Thank You!

Dongwon Park
dong1park@snu.ac.kr

Byung Hyun Lee
ldlqudqus756@snu.ac.kr

Se Young Chun
sychun@snu.ac.kr

https://icl.snu.ac.kr/

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