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

CVPR 2023

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46.5万　2022-12-31

沉沦

作者
安多尼·贝里斯坦
Andoni Beristain

HEX
#5A7C4D
RGB
90,124,77
CMYK
71,45,82,4

HEX
#E3971F
RGB
227,151,31
CMYK
15,49,90,0

HEX
#E9DAAD
RGB
233,218,173
CMYK
13,15,37,0

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阅读

作者

安多尼·贝里斯坦
Andoni Beristain

HEX	RGB	CMYK
#8B5357	139,83,87	53,75,60,7
#123B57	18,59,87	96,80,53,21
#3B6F7C	59,111,124	81,53,48,2

LONG WASHING × 长期洗涤 × bilibili × 饱和度配色

HEX	HEX	HEX
#5B8BAF	#E5A93C	#D7D6D7
RGB	RGB	RGB
91,139,175	229,169,60	215,214,215
CMYK	CMYK	CMYK
69,40,23,0	15,40,81,0	18,15,13,0

LONG WASHING × 长期洗涤 × bilibili × 饱和度配色

花与月

加拿大设计师SOPHIA AHAMED
插画作品《花与月》系列

HEX	HEX	HEX
#182E59	#F9A647	#EDCFAB
RGB 24,46,89	RGB 174,25,8	RGB 215,124,3
CMYK 99,93,48,17	CMYK 39,100,100,5	CMYK 20,61,100,0

LONG WASHING × 长期洗涤 × bilibili × 高级感配色

花与月

加拿大设计师SOPHIA AHAMED
插画作品《花与月》系列

HEX #0F505E	HEX #880A11	HEX #E2B898
RGB 15,80,94	RGB 136,10,17	RGB 226,184,152
CMYK 92,66,57,16	CMYK 48,100,100,23	CMYK 15,33,40,0

Based on

Finding Discriminative Filters for Specific Degradations in Blind Super-Resolution

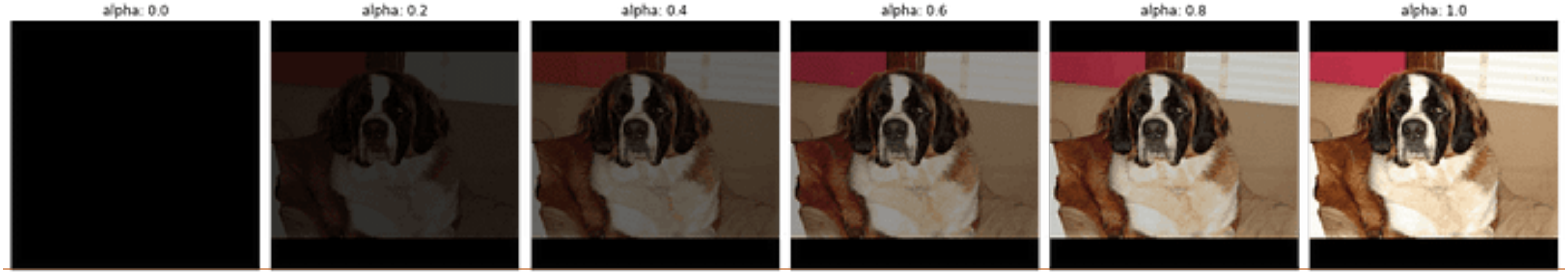
NIPS 2021

Liangbin Xie, Xintao Wang, Chao Dong, Zhongang Qi, Ying Shan

Integrated Gradients

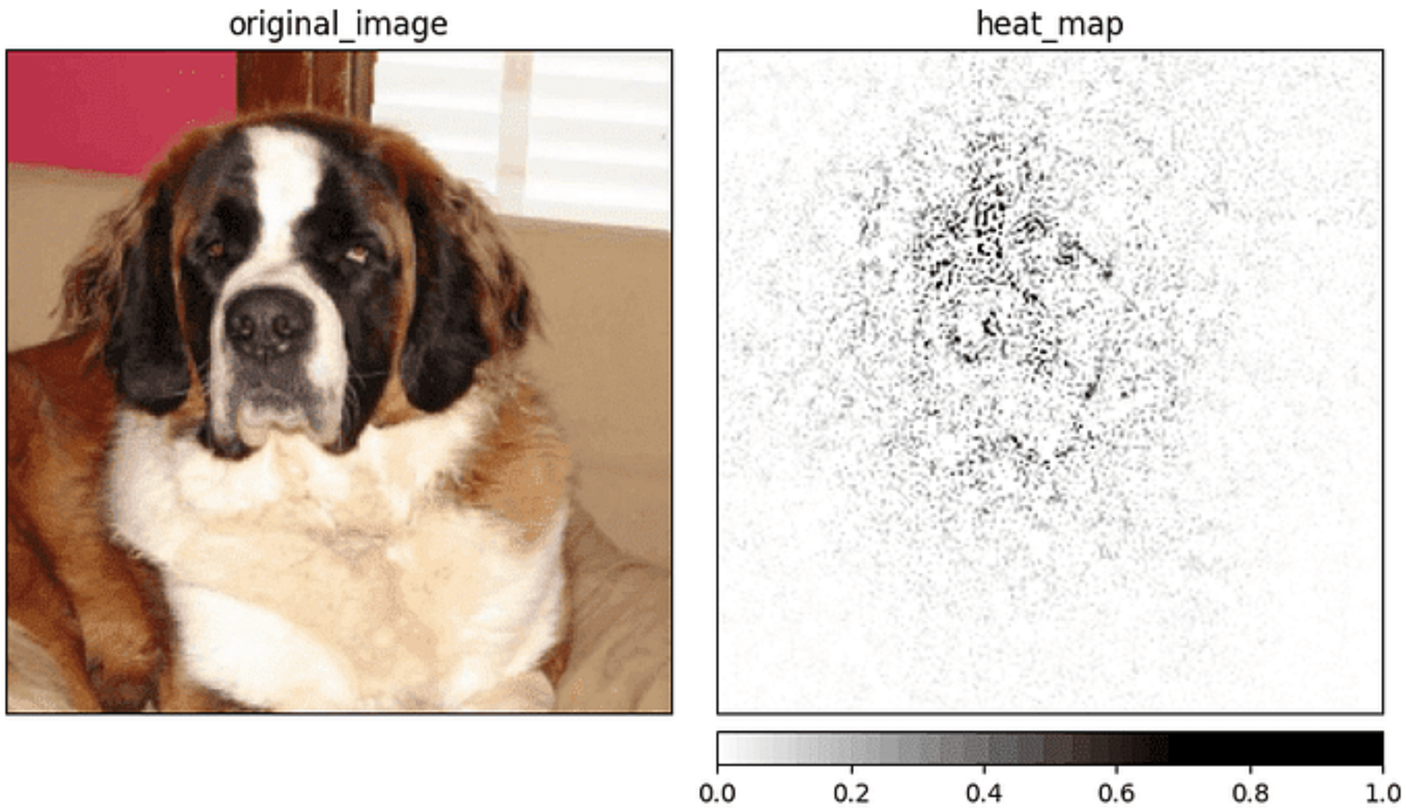
- How to understand DNN?
  - F for model, baseline x’ and the input image x
  - Baseline represents “absence of feature”

$$IntegratedGrads_i(x) ::= (x_i - x'_i) \times \int_{\alpha=0}^{1} \frac{\partial F(x' + \alpha \times (x - x'))}{\partial x_i} d\alpha$$



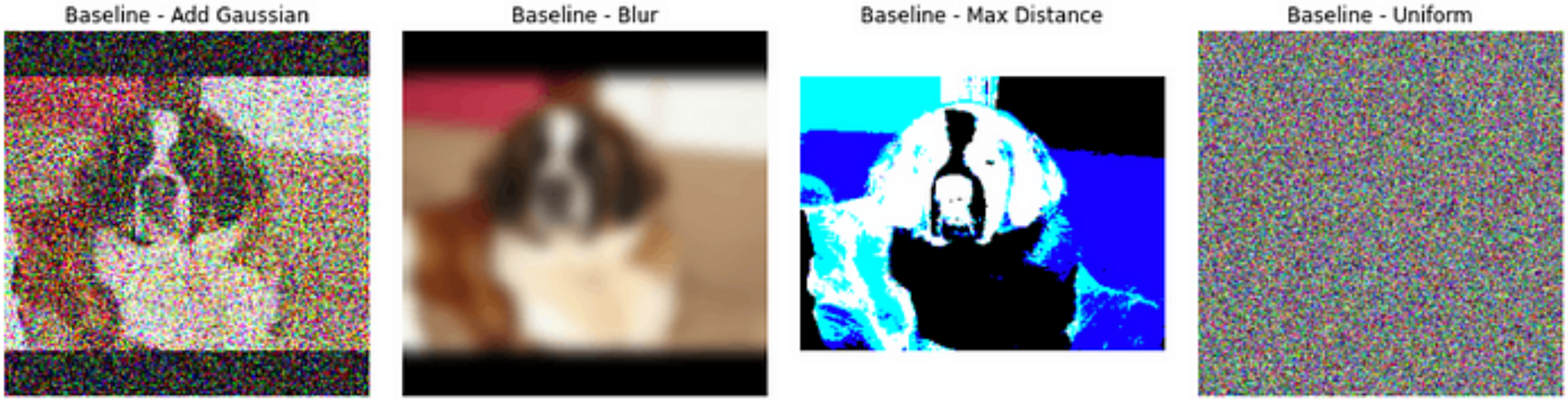
Integrated Gradients

$$IntegratedGrads_i(x) ::= (x_i - x'_i) \times \int_{\alpha=0}^{1} \frac{\partial F(x' + \alpha \times (x - x'))}{\partial x_i} d\alpha$$



Integrated Gradients

$$IntegratedGrads_i(x) ::= (x_i - x'_i) \times \int_{\alpha=0}^{1} \frac{\partial F(x' + \alpha \times (x - x'))}{\partial x_i} d\alpha$$



(a) Gaussian Baseline (b) Blur Baseline (c) Max Distance Baseline (d) Uniform Baseline

FAIG

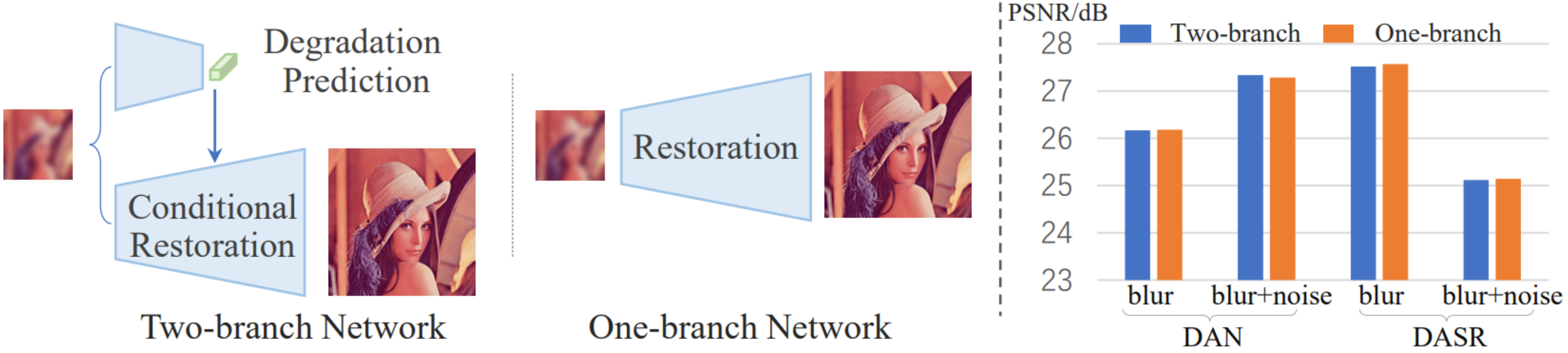
Finding Discriminative Filters for Specific Degradations in Blind Super-Resolution

NIPS 2021

Liangbin Xie, Xintao Wang, Chao Dong, Zhongang Qi, Ying Shan

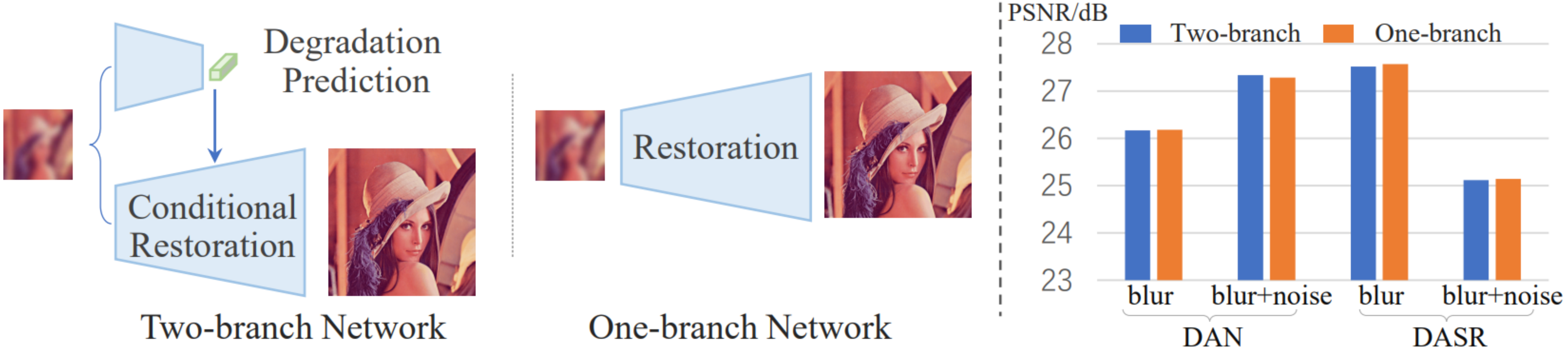
FAIG

- A unified one-branch network achieve comparable performance under similar computation budgets for SOTA blind SR methods

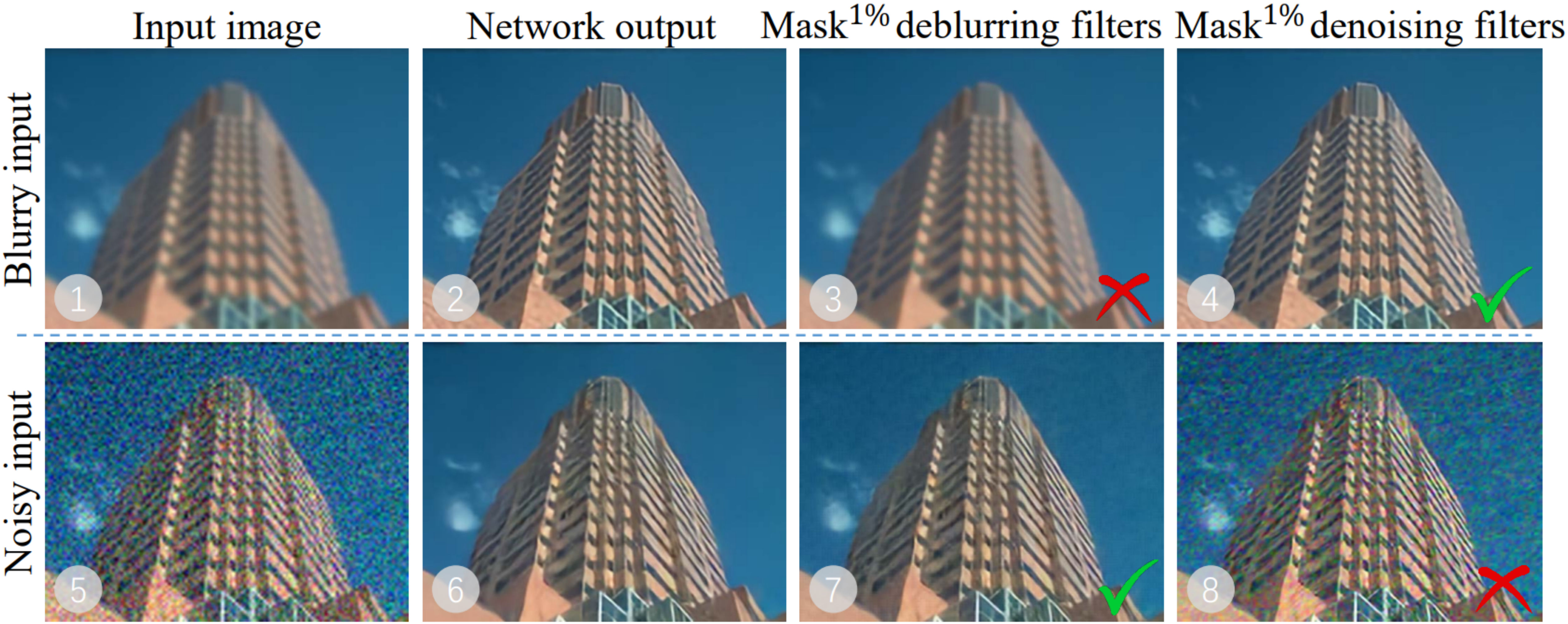


FAIG

- Open the black box
- Are there any small sub-network existing for a specific degradation?



FAIG



Input image
Network output
Mask$^{1\%}$ deblurring filters
Mask$^{1\%}$ denoising filters
Blurry input
Noisy input
1
2
3
4
5
6
7
8

FAIG

- Filter Attribution Integrated Gradients (FAIG)
- Instead of focusing on image, attribute on network parameters

FAIG

L(θ, x) measures the distance between the network output and the ground-truth

$$\mathcal{L}(\theta, x) = \|F(\theta, x) - x^{gt}\|_2^2$$

Let γ(α), α ∈ [0, 1] be a continuous path between the baseline model and the target model, satisfying γ(1) = $\overline{\theta}$, γ(0) = θ, input image x

$$\mathcal{L}(\bar{\theta}, x) - \mathcal{L}(\theta, x) = \mathcal{L}(\gamma(1), x) - \mathcal{L}(\gamma(0), x)$$

$$= \sum_i \int_{\alpha=0}^{1} \frac{\partial \mathcal{L}(\gamma(\alpha), x)}{\partial \gamma(\alpha)_i} \times \frac{\gamma(\alpha)_i}{\partial \alpha} d\alpha$$

FAIG

the i-th dimension (i.e., different network parameters) of the FAIG could be defined as

$$\mathtt{FAIG}_i(\theta, x) = \int_{\alpha=0}^{1} \frac{\partial \mathcal{L}(\gamma(\alpha), x)}{\partial \gamma(\alpha)_i} \times \frac{\gamma(\alpha)_i}{\partial \alpha} d\alpha$$

FAIG

Baseline model:

1. Represent the ‘absence’ of the desired function
2. The output should also be an image with the same content as the input
3. Better to locate in a smaller neighborhood around the target model

First train a common SR model, finetune for blur and noise tasks

FAIG

Problem:

1. The discovered filters do not guarantee to be only responsible for this degradation
2. Calculated for a single input image, influenced by image content

$$\mathtt{FAIG}_i^{\mathcal{D}}(\theta) = \frac{1}{|\mathcal{X}|}\Big(\underbrace{\sum_{x\in\mathcal{X}} |\mathtt{FAIG}_i(\theta, x^{\mathcal{D}})|}_{\text{attribution for degradtion}\mathcal{D}} - \underbrace{\sum_{x\in\mathcal{X}} |\mathtt{FAIG}_i(\theta, x^{\sim\mathcal{D}})|}_{\text{attribution for other degradtions}}\Big),$$

FAIG

Predict the degradation of an input image

$$\mathrm{OS}(x, \mathcal{D}) = \frac{|\{\mathtt{filter}^{\mathcal{D}}\} \cap \{\mathtt{filter}^{x}\}|}{|\{\mathtt{filter}^{x}\}|}.$$

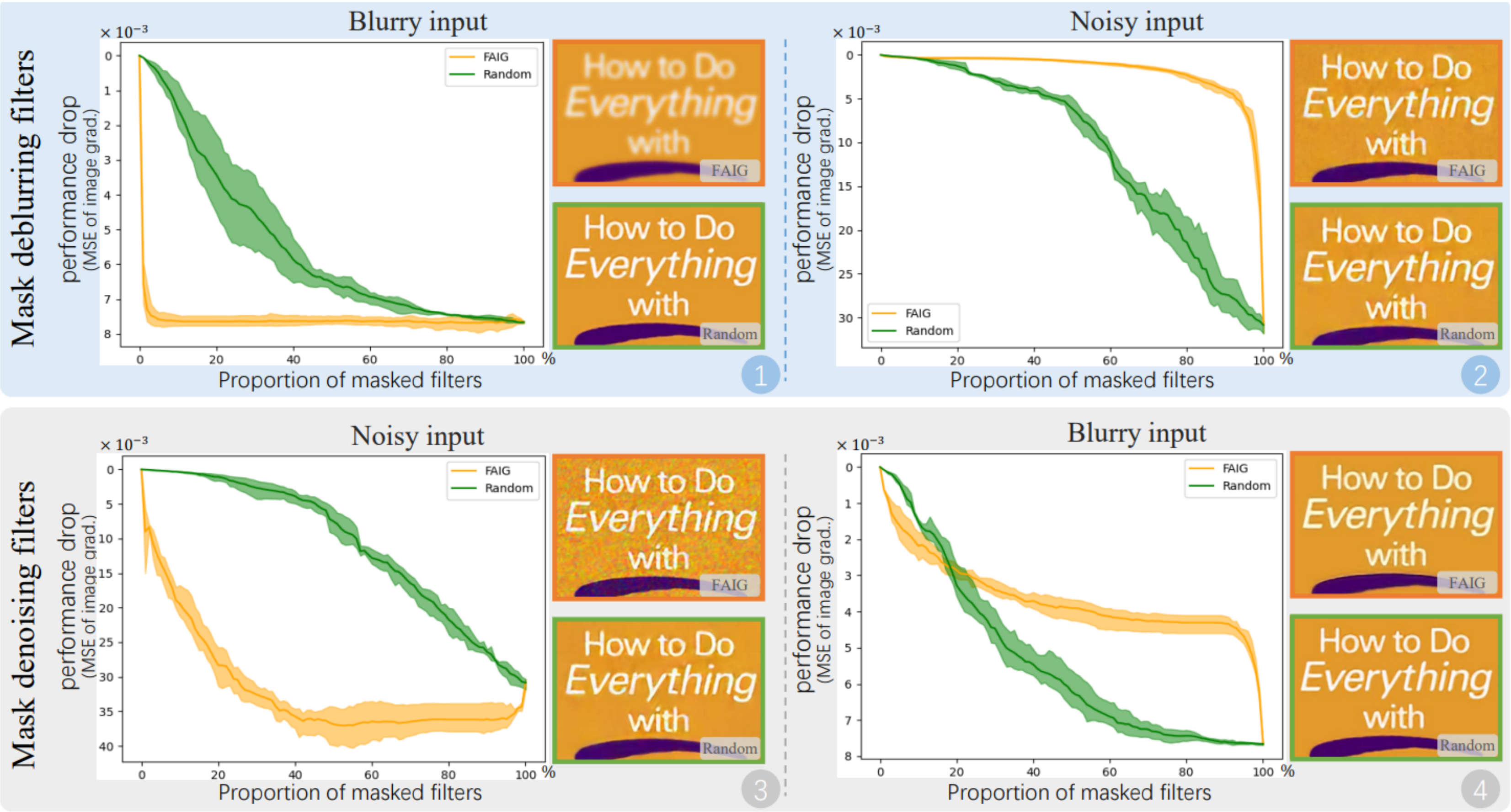
Experiment

Compare the performance drop with other methods

(10^{-3})	mask 1% discovered filters				mask 5% discovered filters			
Input	FAIG (ours)	IG	$\lvert\theta - \bar{\theta}\rvert$	Random	FAIG (ours)	IG	$\lvert\theta - \bar{\theta}\rvert$	Random
Blurry image	**6.68**±0.63	4.31±1.54	0.18±0.13	0.07±0.01	**7.53**±0.24	6.41±0.88	2.16±0.61	0.55±0.32
Noisy image	**6.62**±0.54	4.22±0.44	0.49±0.10	0.04±0.01	**16.28**±3.84	8.01±1.04	3.25±1.85	0.19±0.05

Experiment

Compare the performance drop with other methods



Experiment

Results of re-training baseline models with 1% filters for deblurring and denoising

PSNR(dB) Input	Upper bound	Re-train 1% filters for deblurring				Re-train 1% filters for denoising			
		FAIG	IG	$\lvert\theta - \bar{\theta}\rvert$	Random	FAIG	IG	$\lvert\theta - \bar{\theta}\rvert$	Random
Blurry	29.203 (±0.021)	**27.889** (±0.207)	26.389 (±0.274)	26.444 (±0.097)	26.691 (±0.092)	27.642 (±0.007)	26.534 (±0.125)	26.444 (±0.096)	26.668 (±0.126)
Noisy	26.712 (±0.008)	25.268 (±0.035)	25.211 (±0.005)	25.288 (±0.044)	25.239 (±0.034)	**25.743** (±0.033)	25.141 (±0.116)	25.275 (±0.035)	25.204 (±0.016)

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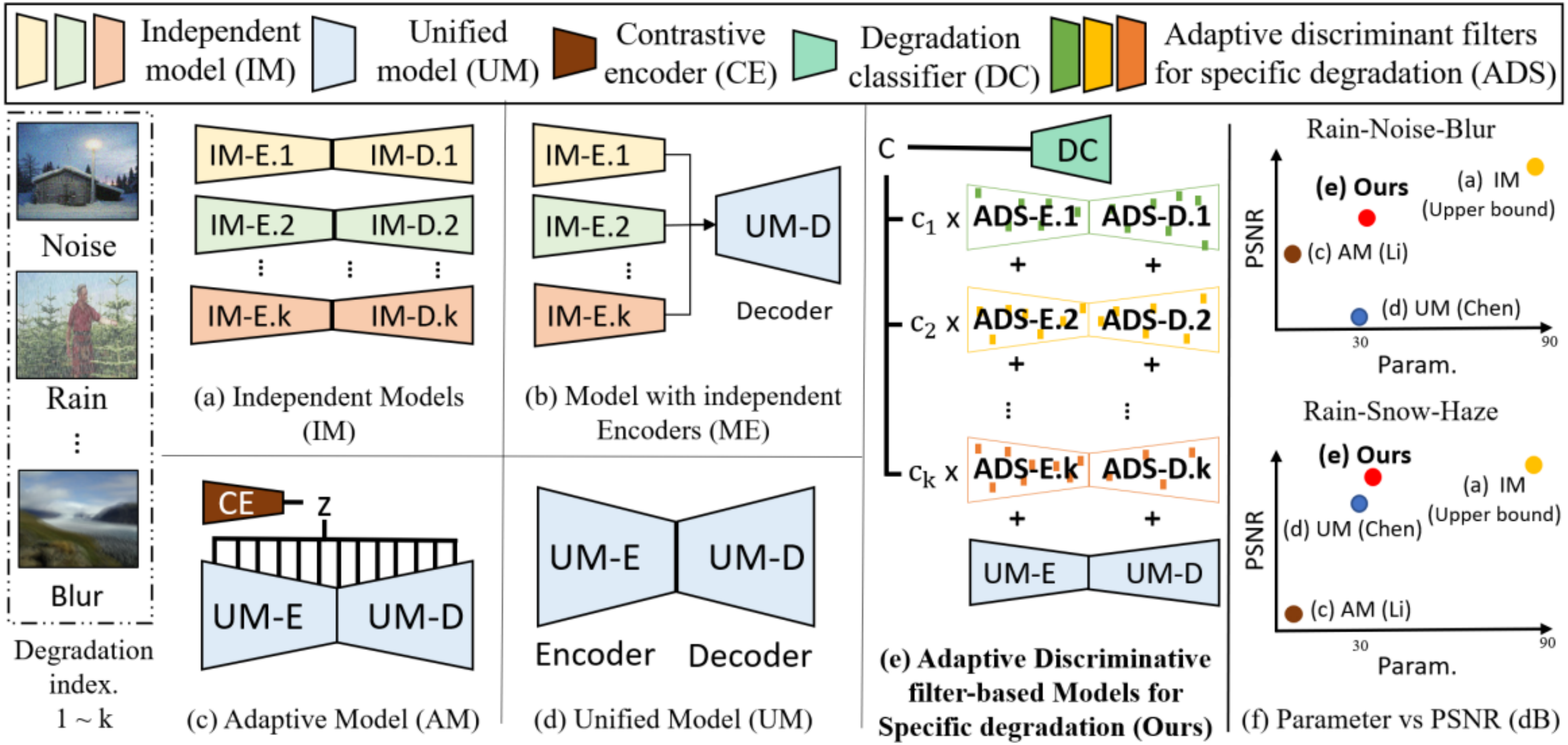
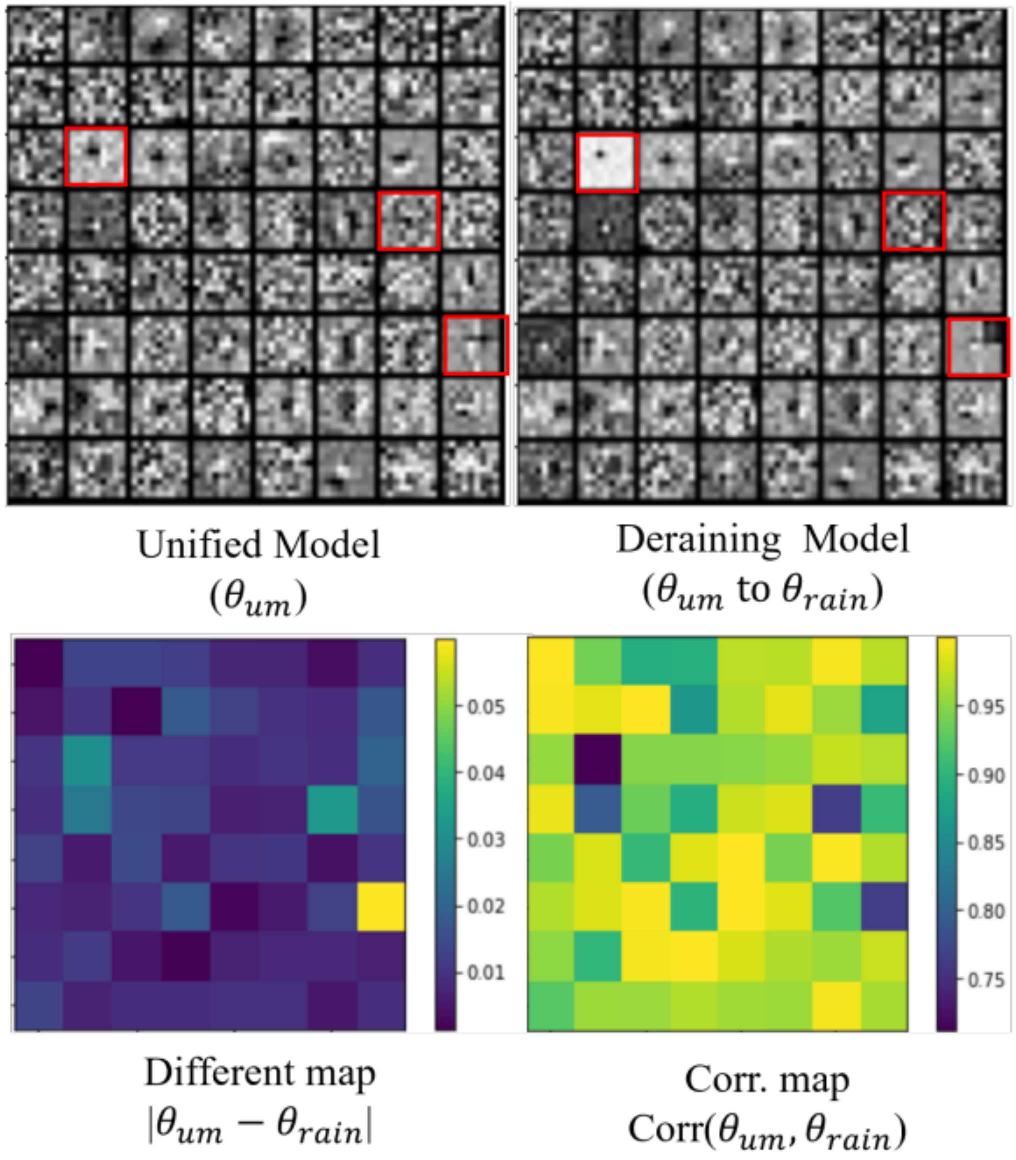
ADMS



Independent model (IM)
Unified model (UM)
Contrastive encoder (CE)
Degradation classifier (DC)
Adaptive discriminant filters for specific degradation (ADS)
Noise
Rain
Blur
Degradation index. 1 ~ k
IM-E.1 IM-D.1
IM-E.2 IM-D.2
IM-E.k IM-D.k
(a) Independent Models (IM)
UM-D
Decoder
(b) Model with independent Encoders (ME)
CE
z
UM-E UM-D
(c) Adaptive Model (AM)
Encoder Decoder
(d) Unified Model (UM)
C
DC
c1 x ADS-E.1 ADS-D.1
c2 x ADS-E.2 ADS-D.2
ck x ADS-E.k ADS-D.k
(e) Adaptive Discriminative filter-based Models for Specific degradation (Ours)
Rain-Noise-Blur
Rain-Snow-Haze
PSNR
Param.
(e) Ours
(a) IM (Upper bound)
(c) AM (Li)
(d) UM (Chen)
30
90
(f) Parameter vs PSNR (dB)

ADMS

- Visualization of convolution filters in UM for Rain-Noise-Blur and IM for Rain, where IM was fine-tuned from UM\
- Only a small number of filters changed



ADMS

- the baseline model is the unified model trained for all degradations
- the target model for the specific degradation d is constructed by fine-tuning

the baseline model.

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

ADMS

- the baseline model is the unified model trained for all degradations
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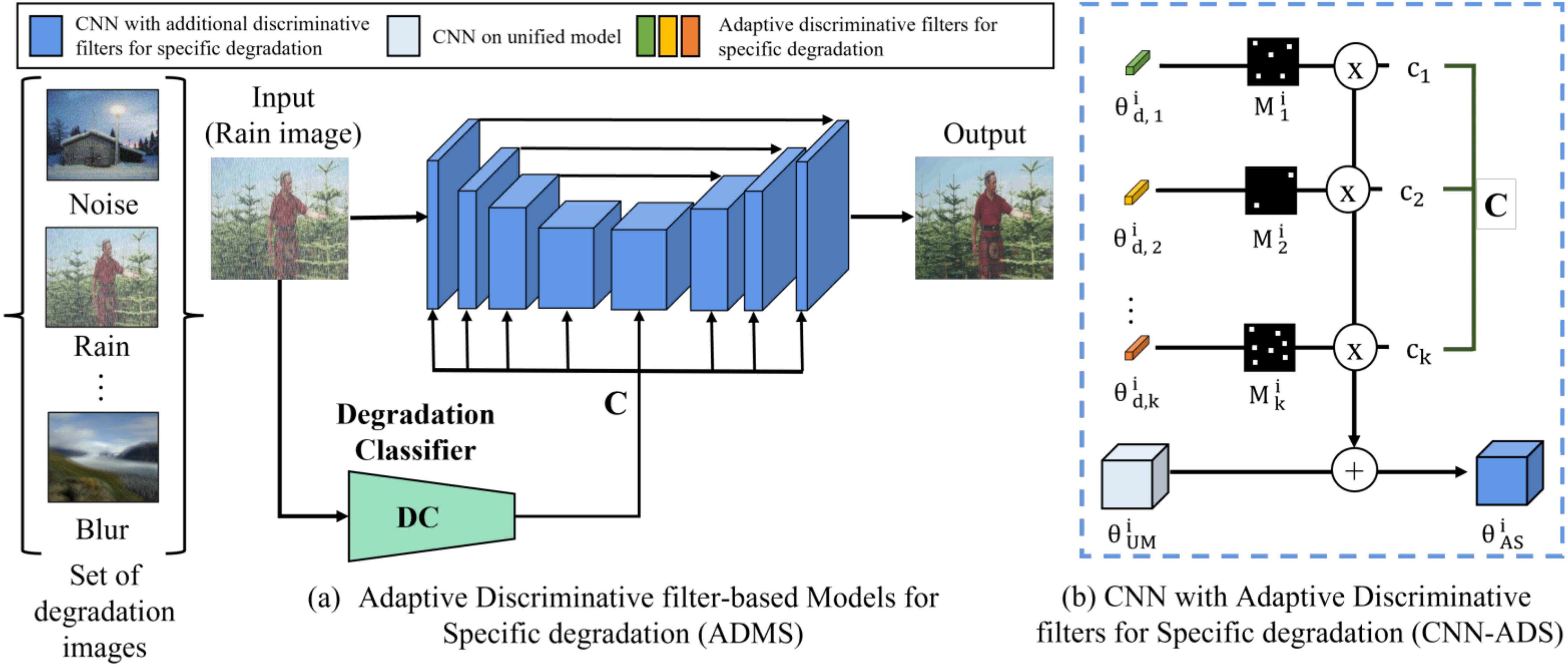
the baseline model.

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

ADMS



(a) Adaptive Discriminative filter-based Models for Specific degradation (ADMS)

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

ADMS

- the baseline model is the unified model trained for all degradations
- the target model for the specific degradation d is constructed by fine-tuning

the baseline model.

the adaptive network kernel θ_{ads} is defined as follows

$$\theta^{i}_{ads} = \theta^{i}_{um} + \sum_{d=1}^{k} \hat{c}_d \, \theta^{i}_{d} \odot M^{i}_{d}$$

C is the predicted degradation type where the sum of all $\hat{c}_d$ is 1 and each $\hat{c}_d$ is in between 0 and 1

Experiment

- Quantitative performance comparison on the Rain-Blur-Noise test dataset

Net	M	Rain	Blur	Noise	Avg.	Par.
NAF	IM	33.03	30.30	31.59	31.64	**51.3**
MSB	IM	33.02	28.79	31.52	31.11	**83.1**
NAF	UM	32.99	29.46	31.39	31.28	17.1
MSB	UM	32.12	26.61	30.97	29.90	28.7
M-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	30.25	7.6
NAF	**Ours**	**33.15**	**29.99**	**31.53**	**31.56**	18.9
MSB	**Ours**	**32.74**	**27.56**	**31.42**	**30.58**	31.6

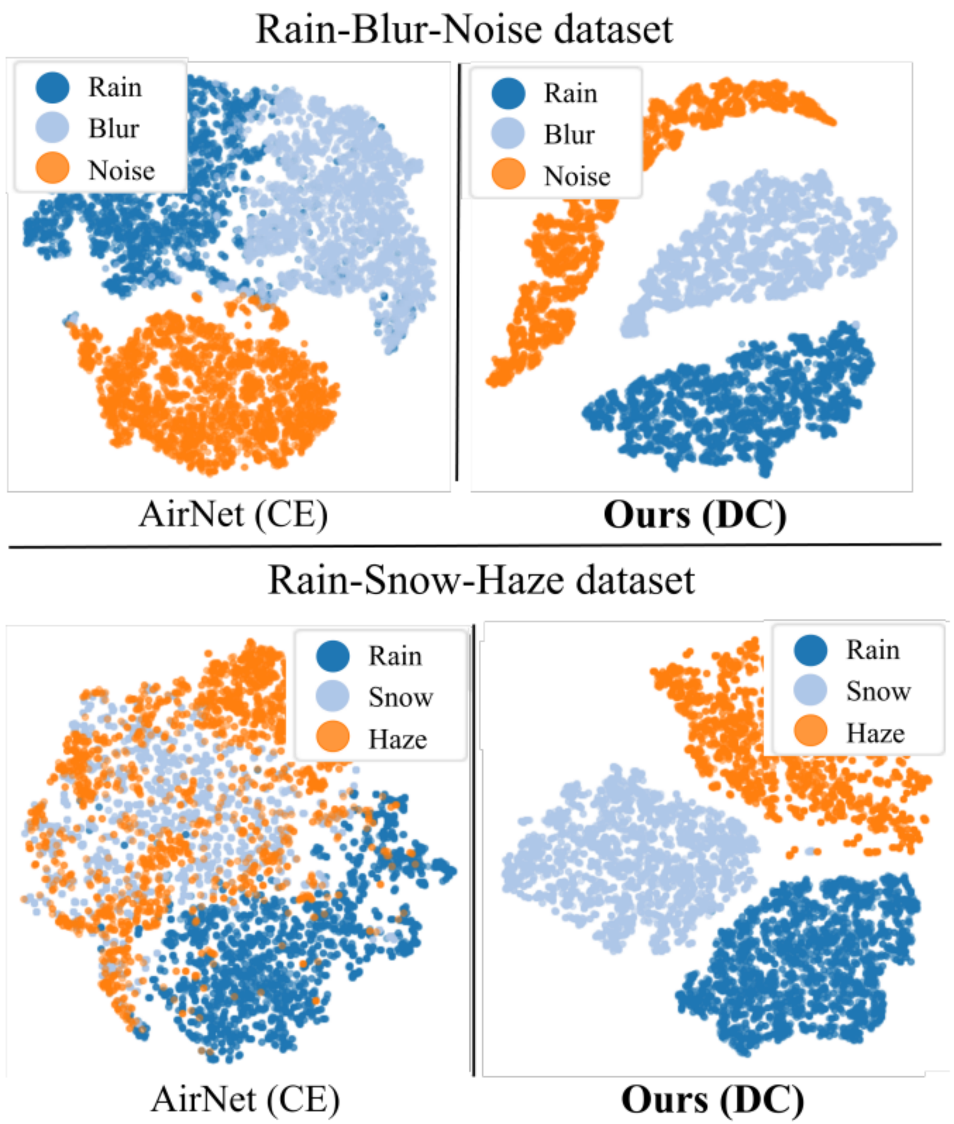
Experiment

- Quantitative performance comparison on the Rain-Snow-Hazy test dataset

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

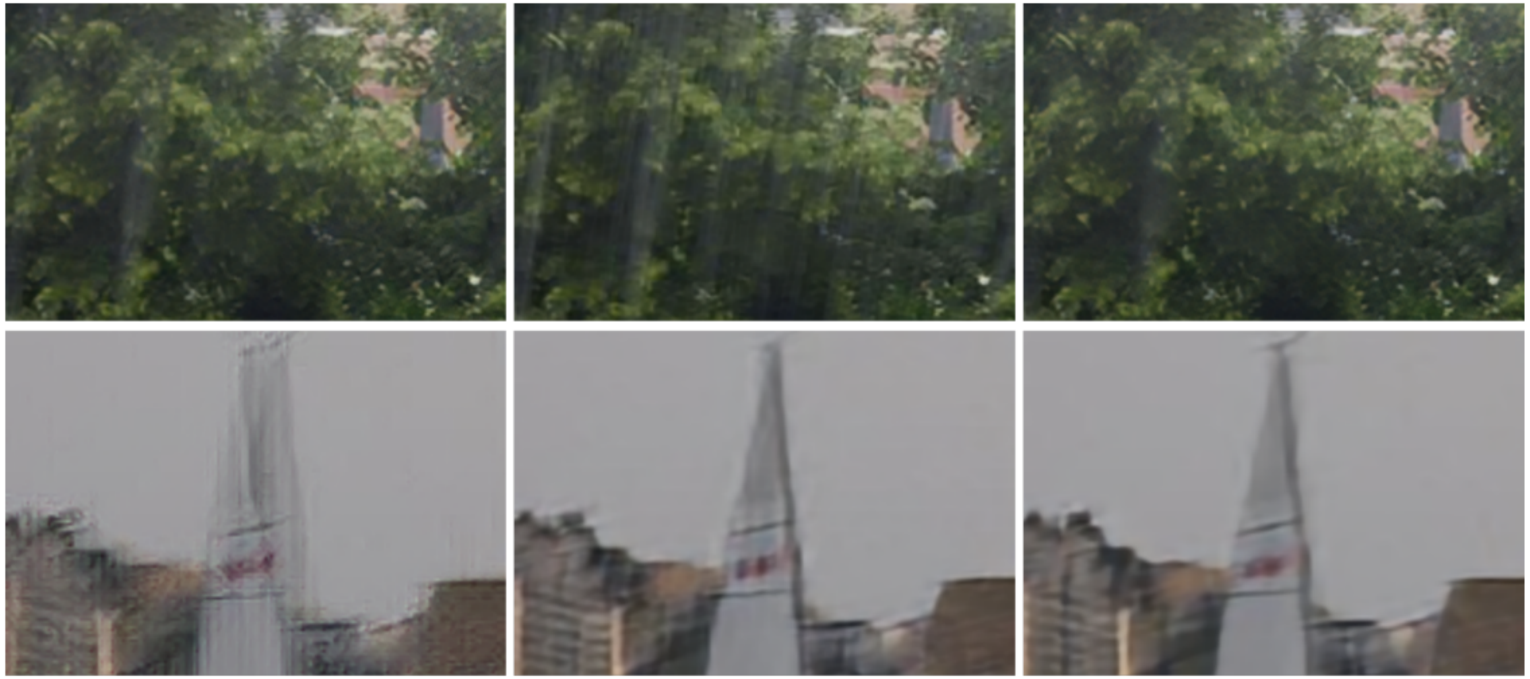
Experiment

- Visualization of representations for degradation types



Experiment

- Real data



Chen Airnet **Ours**

Conclusion

- Introduce FAIG, a method to attribute performance on network
- The application on multi-degradation tasks

Thanks for your listening!