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Finding Discriminative Filters for Specific Degradations in Blind Super-Resolution

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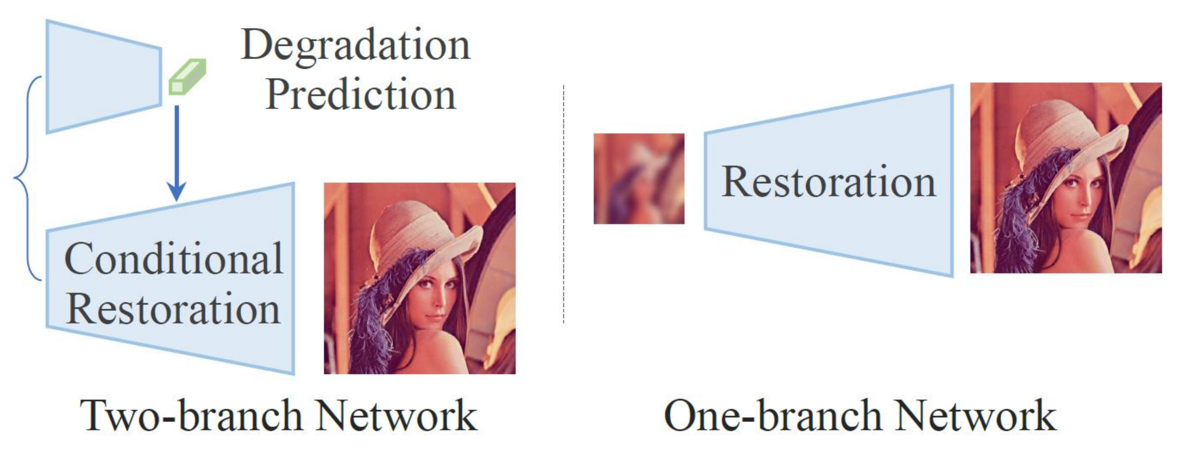
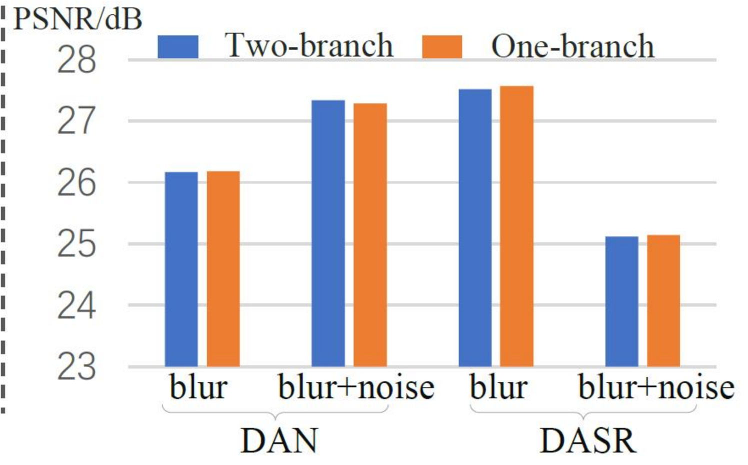
The mechanism of Blind SR Network

Motivation

A unified one-branch network could achieve comparable performance to the two-branch scheme under similar computation budgets.



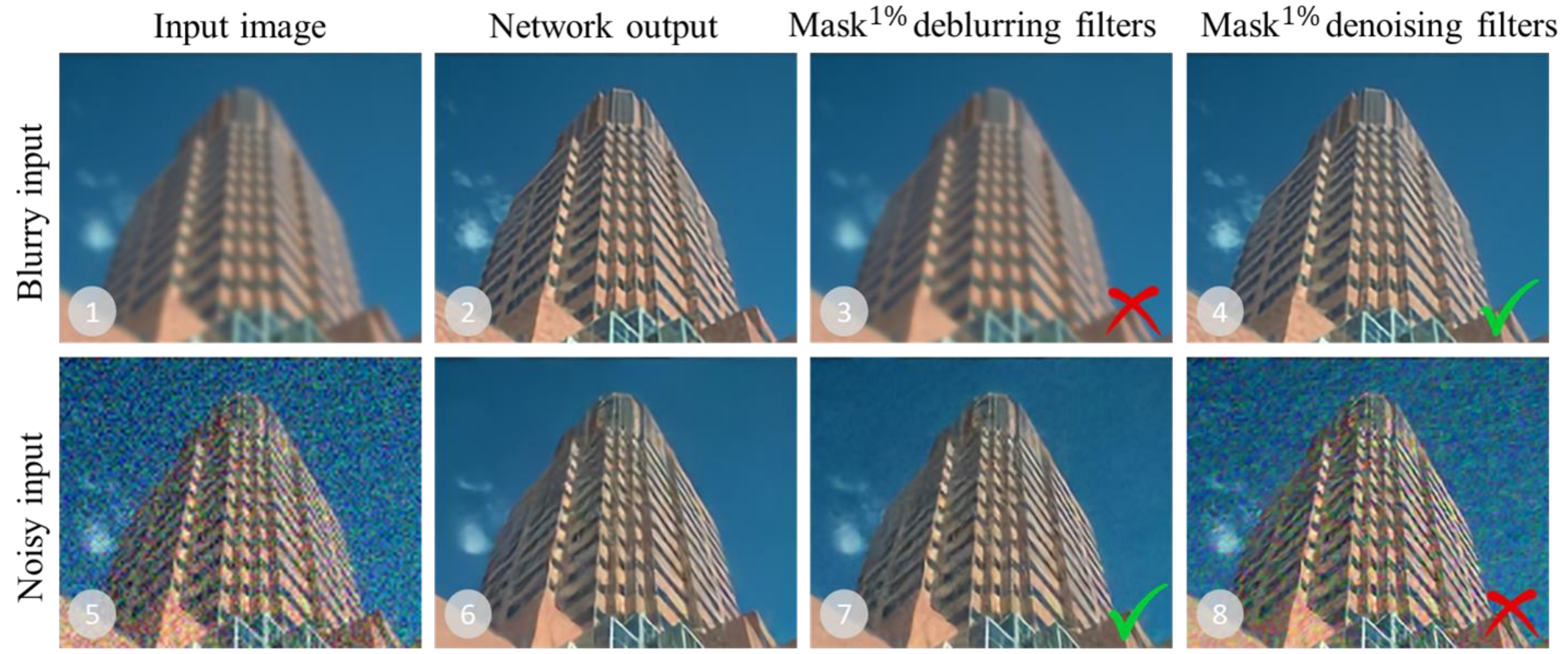


Two key questions are investigated

- Could one-branch networks automatically learn to distinguish degradations as what we specially design in two-branch methods?
- Are there any small sub-network (i.e., a set of filters) existing for a specific degradation?

A diagnostic tool—Filter Attribution Integrated Gradients (FAIG)

In this work, we propose Filter Attribution method based on Integral Gradient (FAIG) to find core filters in a network that make the greatest contribution to the function of a specific degradation removal.

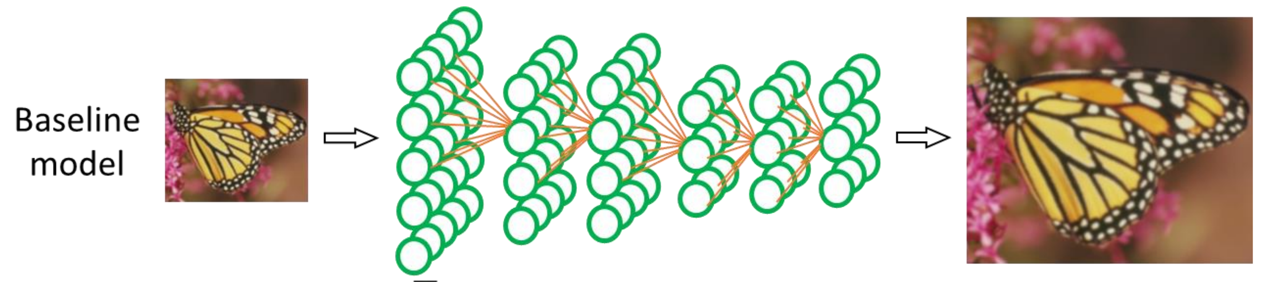


When we mask these discovered filters for a specific degradation, the corresponding function is eliminated, while functions for other degradations are maintained

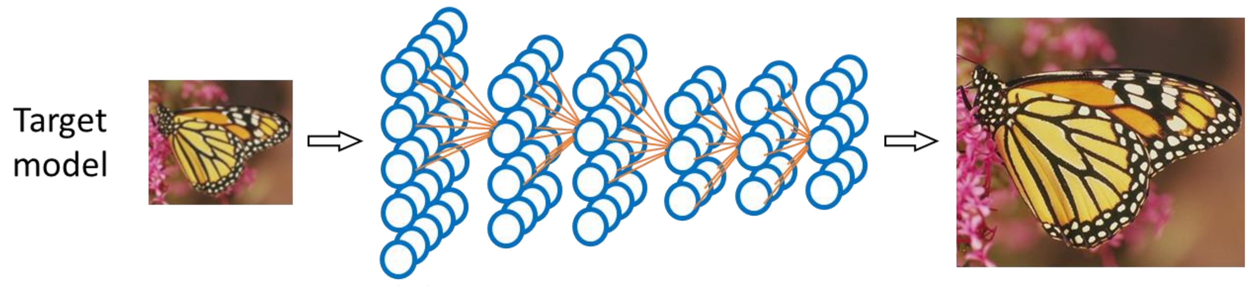
Filter Attribution Integrated Gradient (FAIG)

Key idea

Given the same input, the changes of the network output can be attributed to the changes of network parameters (i.e., filters).



The ***baseline network*** $F(\bar{\theta})$ is a pure SR network that cannot remove blur.



The ***target network*** $F(\theta)$ is a re-trained network that can remove blur.

Find important filters for one degradation

We first quantify the network function of degradation removal by

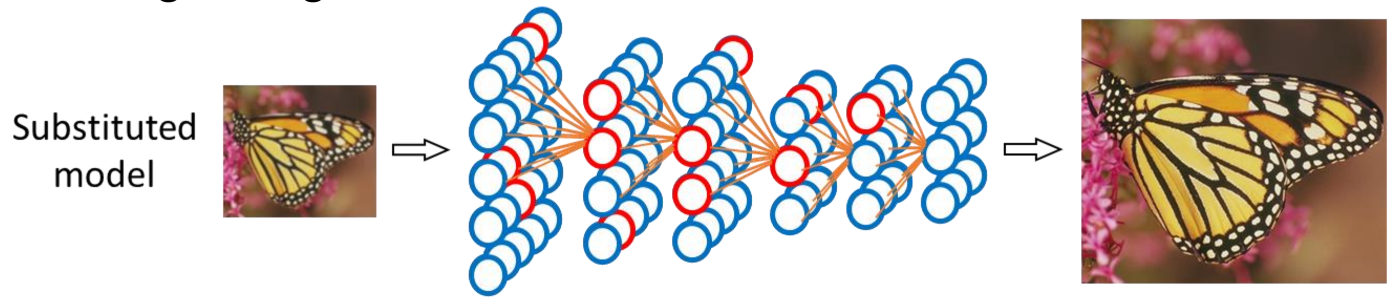
$$\mathcal{L}(\theta, x) = \| F(\theta, x) - x^{gt} \|_2^2$$

Motivated by Integrated Gradient(IG) that accumulates the gradients at all points along a straight-line path, we accumulate gradients along a path

$$\gamma(\alpha) = \bar{\theta} + \alpha \times (\theta - \bar{\theta})$$

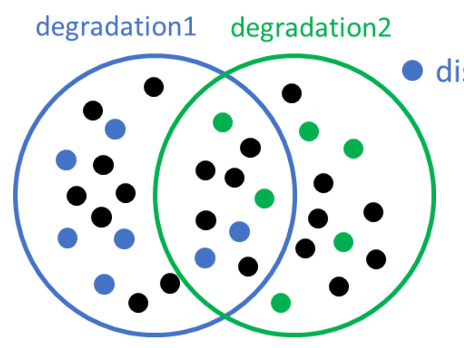
$$\mathrm{FAIG}_i(\theta, x) = \int_{\alpha=0}^{1} \frac{\partial \mathcal{L}(\gamma(\alpha), x)}{\partial \gamma(\alpha)_i} \times \frac{\gamma(\alpha)_i}{\partial \alpha} d\alpha$$

The filters with highest gradient are the most discriminative filters



The ***substituted network*** loses the deblur function.

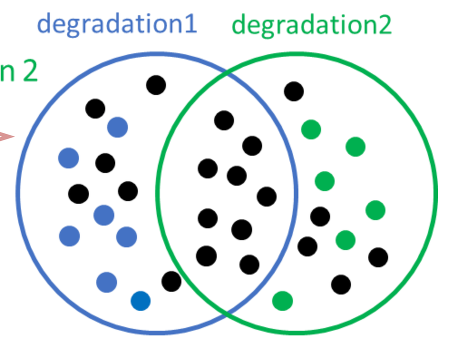
Find Discriminative filters for specific degradation



FAIG

● discovered filters for degradation 1 ● discovered filters for degradation 2

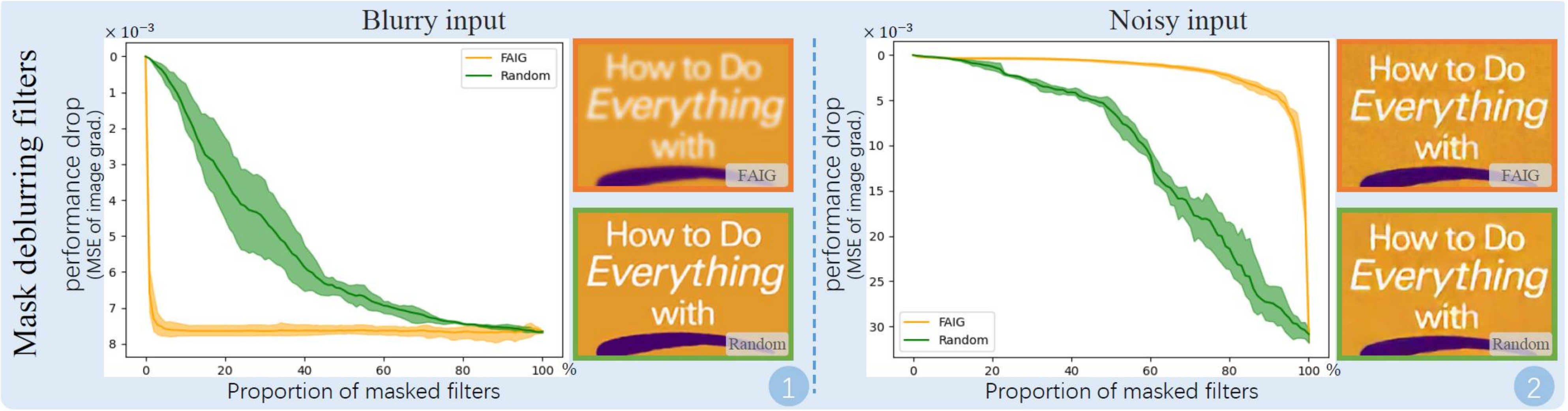
$$\mathrm{FAIG}_i^{\mathcal{D}}(\theta) = \frac{1}{|\mathcal{X}|}\Big(\underbrace{\sum_{x\in\mathcal{X}} |\mathrm{FAIG}_i(\theta, x^{\mathcal{D}})|}_{\text{attribution for degradation } \mathcal{D}} - \underbrace{\sum_{x\in\mathcal{X}} |\mathrm{FAIG}_i(\theta, x^{\sim\mathcal{D}})|}_{\text{attribution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



FAIG with gradient elimination

Experiments

Mask discovered filters



When we mask FAIG-discovered filters for deblurring (even a very small portion), the performance for deblurring drops drastically while the function of denoising is maintained. While the randomly selected filters are non-discriminative

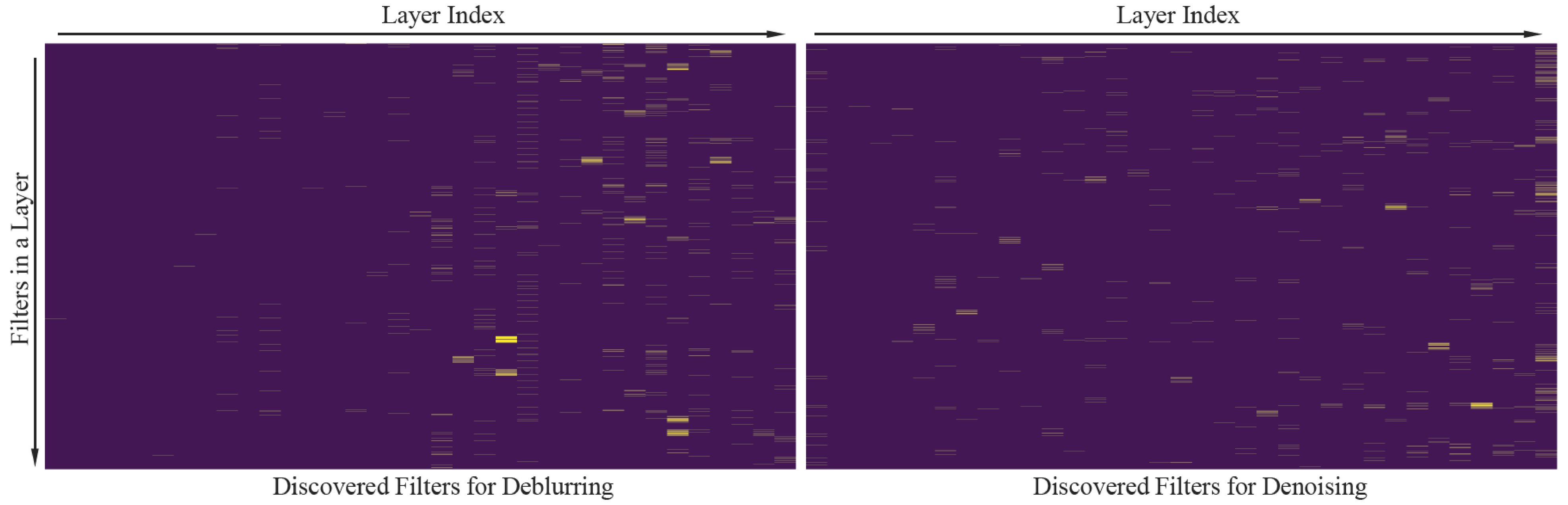
(10^{-3})	mask 1% discovered filters				mask 5% discovered filters			
Input	FAIG (ours)	IG	$\lvert\theta-\bar{\theta}\rvert$	Random	FAIG (ours)	IG	$\lvert\theta-\bar{\theta}\rvert$	Random
Blurry image	**6.68**±0.63	4.31±1.54	0.18±0.13	0.07±0.01	**7.53**±0.24	6.41±0.88	2.16±0.61	0.55±0.32
Noisy image	**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

Distribution of discovered filters in a network

PSNR(dB)		Re-train 1% filters for deblurring				Re-train 1% filters for denoising			
Input	Upper bound	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)

The locations and connections of discovered filters also have discriminative characteristics for specific degradations

Distribution of discovered filters in a network



The deblurring filters are more located in the back part of the network while denoising filters locate more uniformly

code: https://github.com/TencentARC/FAIG group: https://xpixel.group/