Universal Image Restoration Pre-training via Degradation Classification

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Restoration model can classify degradation

Preliminary experiment:

- Given restoration models trained on **three** degradation.
  (haze, rain, Gaussian noise)
- Their features are required to classify **five** degradation.
  (haze, rain, Gaussian noise, *motion blur,* and *low-light*)

Methods	NAFNet	SwinIR	Restormer	PromptIR
Acc. on Random initialized (%)	52 ± 1	64 ± 4	71 ± 4	55 ± 3
Acc. on 3D all-in-one trained 200k iterations (%)	90 ± 5	92 ± 6	93 ± 3	93 ± 5
Acc. on 3D all-in-one trained 400k iterations (%)	94 ± 4	95 ± 4	95 ± 4	95 ± 4
Acc. on 3D all-in-one trained 600k iterations (%)	94 ± 5	95 ± 4	97 ± 2	95 ± 4

Results:

- **Randomly initialized** models can achieve 52 ~ 71 % degradation classification accuracy.
- **After the 3D all-in-one training**, models achieve an accuracy of 94% or higher in classifying degradation, including **unseen** ones.

Visualization: T-SNE results of PromptIR on five degradation after random initialization and 3D all-in-one training.
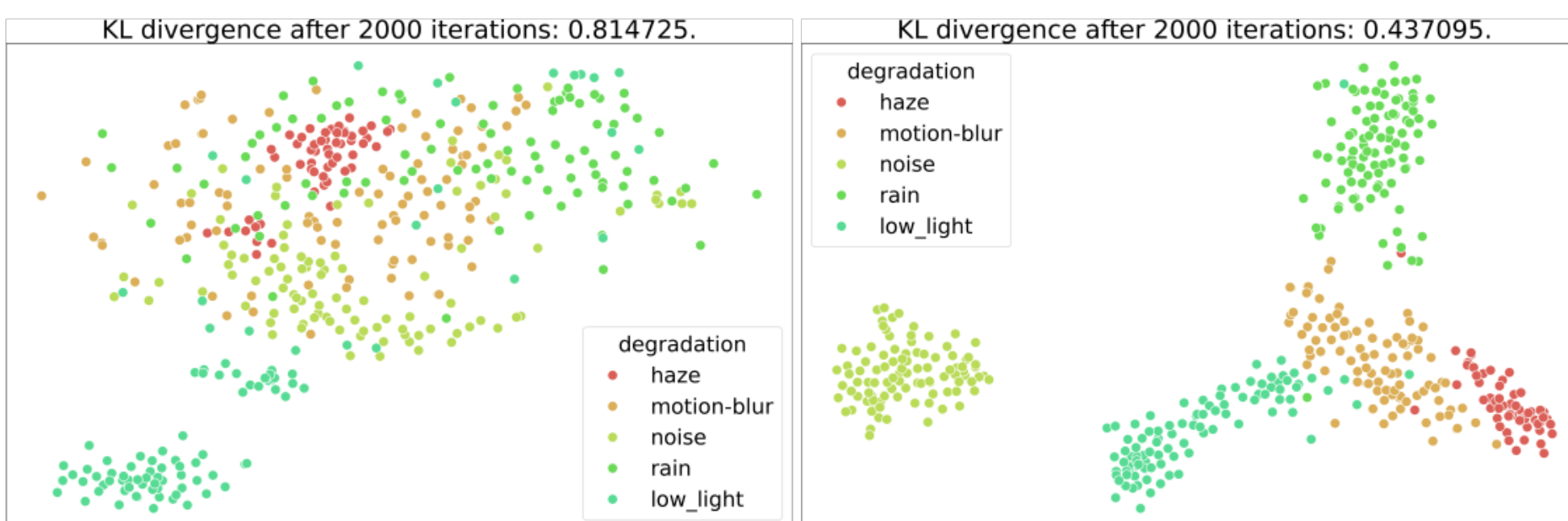

Conclusions:

- Randomly initialized models demonstrate an inherent capability to classify degradation.
- Models trained on the all-in-one task exhibit the ability to discern unkown degradation.
- There is a degradation understanding step in the early training of the restoration model.

Motivation:

!!! bringing the degradation classification stage forward !!!

DCPT: Degradation Classification Pre-Training

DCPT combines **degradation discrimination** and **generation** in single restoration model.

(a) Degradation classification stage. (b) Generation stage.
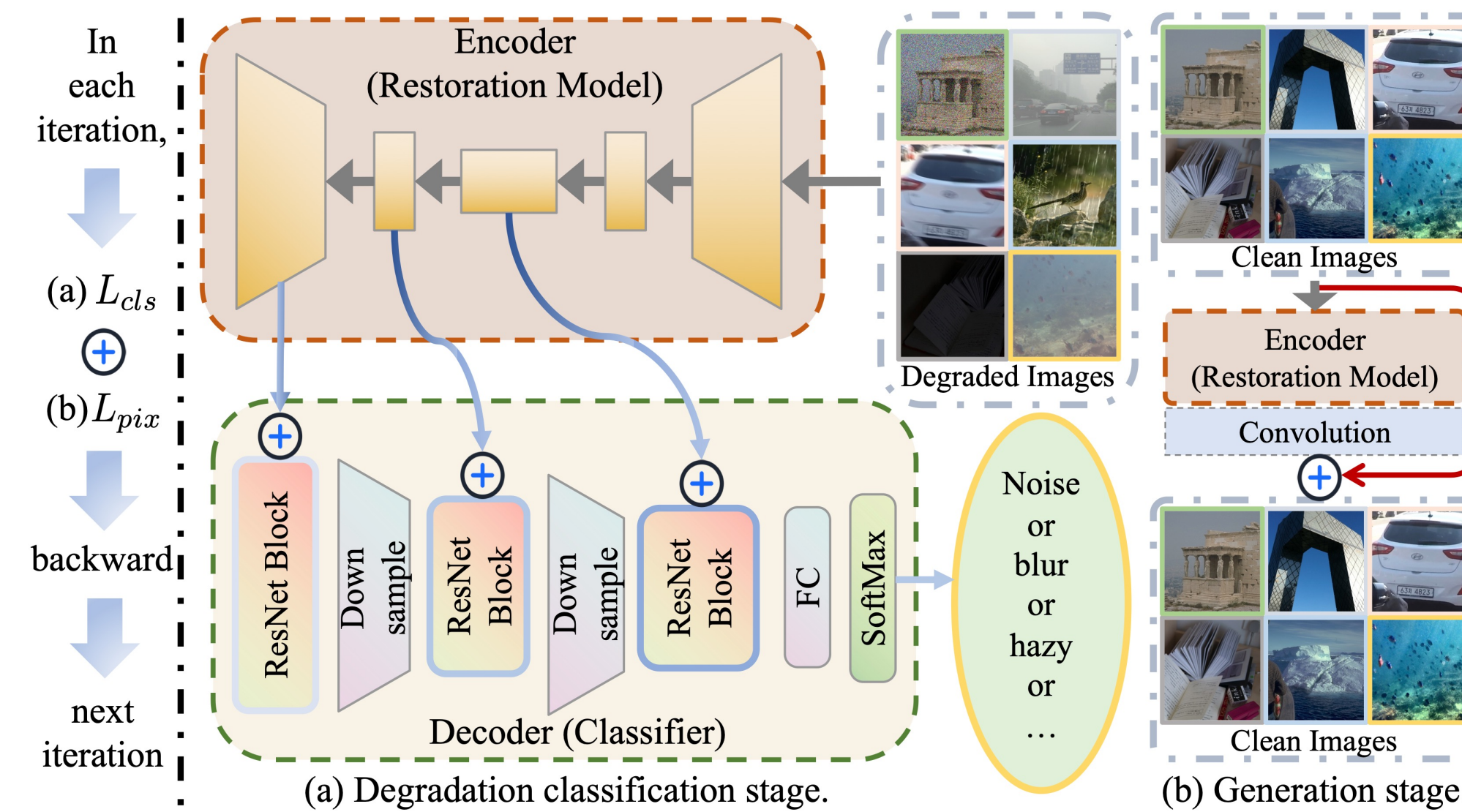
Quantitative Results: Universal image restoration

1. Applicable to **various network structures.** DCPT consistently achieves average PSNR improvements of **2.08 dB and above**.
2. Archiving **SoTA performance** in all-in-one restoration.
3. More **efficient than other degradation embedding**, *e.g.,* physical degradation models (IDR) and human instructs (InstructIR).

Method	Dehazing PSNR↑ / SSIM↑	Deraining PSNR↑ / SSIM↑	Denoising PSNR↑ / SSIM↑	Deblurring PSNR↑ / SSIM↑	Low-Light PSNR↑ / SSIM↑	Average PSNR↑ / SSIM↑
AirNet	21.04 / 0.884	32.98 / 0.951	30.91 / 0.882	24.35 / 0.781	18.18 / 0.735	25.49 / 0.846
IDR	25.24 / 0.943	35.63 / 0.965	31.60 / 0.887	27.87 / 0.846	21.34 / 0.826	28.34 / 0.893
InstructIR	27.10 / 0.956	36.84 / 0.973	31.40 / 0.887	29.40 / 0.886	23.00 / 0.836	29.55 / 0.907
SwinIR	21.50 / 0.891	30.78 / 0.923	30.59 / 0.868	24.52 / 0.773	17.81 / 0.723	25.04 / 0.835
DCPT-SwinIR	**28.67 / 0.973**	**35.70 / 0.974**	**31.16 / 0.882**	**26.42 / 0.807**	**20.38 / 0.836**	**28.47 / 0.894**
NAFNet	25.23 / 0.939	35.56 / 0.967	31.02 / 0.883	26.53 / 0.808	20.49 / 0.809	27.76 / 0.881
DCPT-NAFNet	**29.47 / 0.971**	**35.68 / 0.971**	**31.31 / 0.886**	**29.22 / 0.883**	**23.52 / 0.855**	**29.84 / 0.914**
Restormer	24.09 / 0.927	34.81 / 0.962	31.49 / 0.884	27.22 / 0.829	20.41 / 0.806	27.60 / 0.881
DCPT-Restormer	**29.86 / 0.973**	**36.68 / 0.975**	**31.46 / 0.888**	**28.95 / 0.879**	**23.26 / 0.842**	**30.04 / 0.911**
PromptIR	25.20 / 0.931	35.94 / 0.964	31.17 / 0.882	27.32 / 0.842	20.94 / 0.799	28.11 / 0.883
DCPT-PromptIR	**30.72 / 0.977**	**37.32 / 0.978**	**31.32 / 0.885**	**28.84 / 0.877**	**23.35 / 0.840**	**30.31 / 0.911**
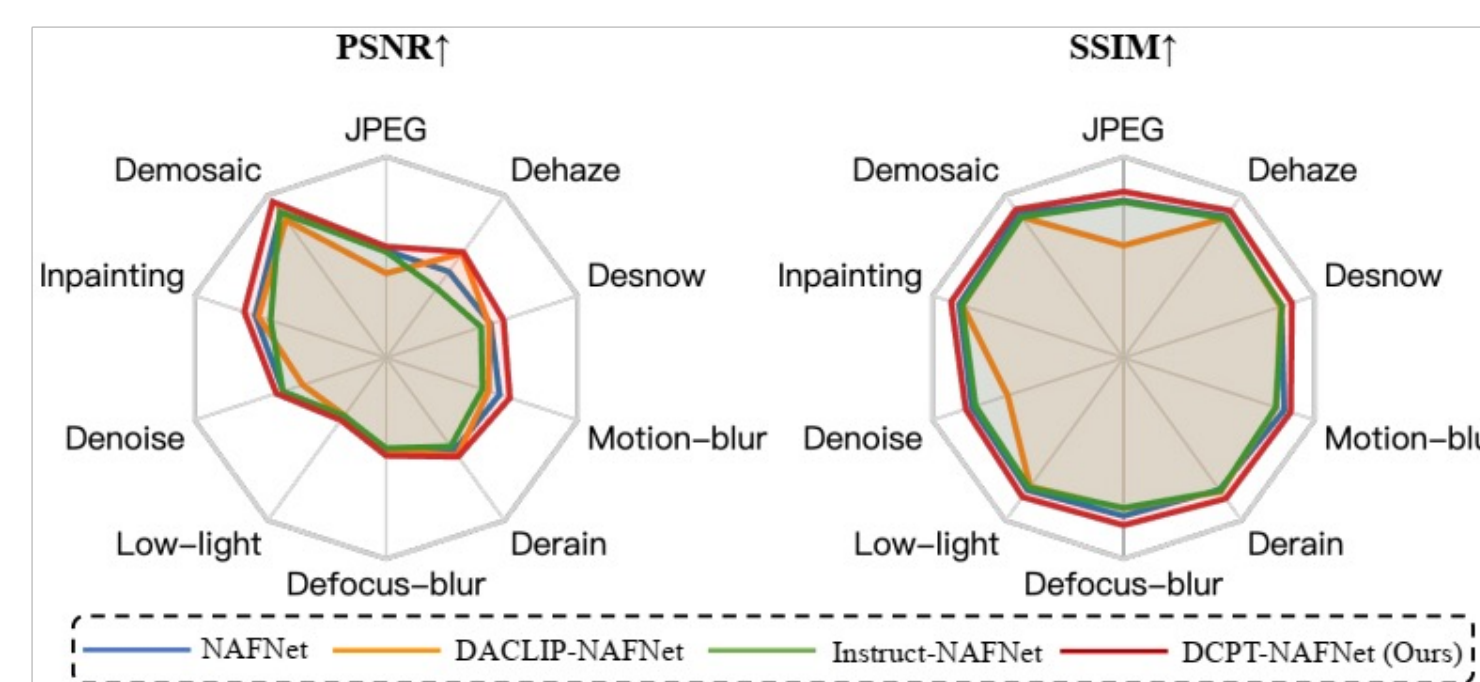
Method	10D-Average PSNR↑/SSIM↑
AirNet	26.41 / 0.842
TransWeather	22.83 / 0.779
WeatherDiff	24.60 / 0.793
PromptIR	27.93 / 0.851
DiffUIR-L	28.75 / 0.869
NAFNet	27.17 / 0.837
+DACLIP	27.42 / 0.798
+Instruct	28.30 / 0.862
+DCPT (Ours)	**29.72 / 0.888**

Decoder helps cross-degradation generalization

Unlike previous pre-training methods, our decoder is not discarded.

In **DC-guided training**, the role of the decoders is limited to classifying the input images into two categories: **clean** and **degraded**.
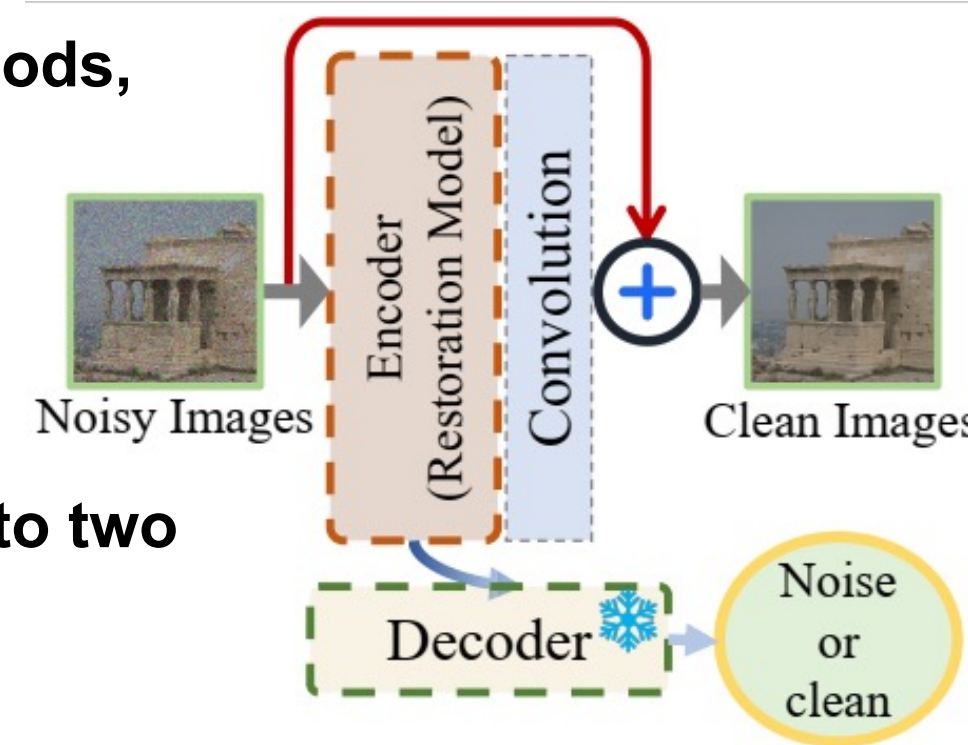
DC-guided training achieves greater performance gains on tasks that are more difficult to generalize to.

DC-guided	Target task	Denoise		Deblur		Derain	
	Source task	Deblur	Derain	Denoise	Derain	Denoise	Deblur
✗	PSNR ↑	31.50	31.65	25.44	27.51	31.99	32.85
✓	PSNR ↑	31.62	31.69	30.36	28.79	36.29	35.77
Supervised	PSNR ↑	31.78		32.92		36.74	

Qualitative Results: Universal image restoration

Our codes and trained model weights are available at https://github.com/MILab-PKU/dcpt.