DDR: Exploiting Deep Degradation Response as Flexible Image Descriptor

Juncheng Wu[1,3], Zhangkai Ni[1*], Hanli Wang[1], Wenhan Yang[2], Yuyin Zhou[3], Shiqi Wang[4]

[1]Tongji University; [2]Peng Cheng Laboratory; [3]UC Santa Cruz; [4]City University of Hong Kong

Code: https://github.com/eezkni/DDR

Background

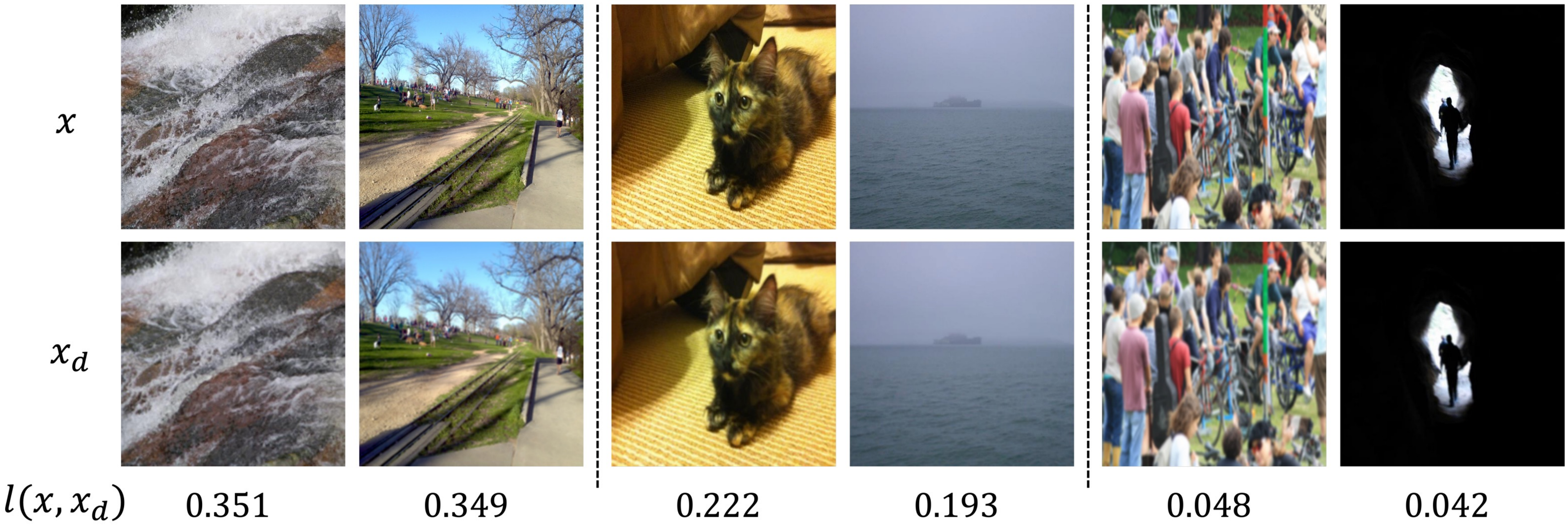
- **Image descriptors:** quantifying fundamental visual features of images.
  - Descriptors for texture, color, complexity, and quality.

- **Deep features extracted by pre-trained neural networks**
  - **Encode rich visual representations**, widely applied in low-level vision tasks including image restoration and image quality assessment
  - **Many existing image descriptors regress the deep features of an image to a score,** by minimizing the loss between predicted scores and the ground truth scores labelled by humans.

Motivation

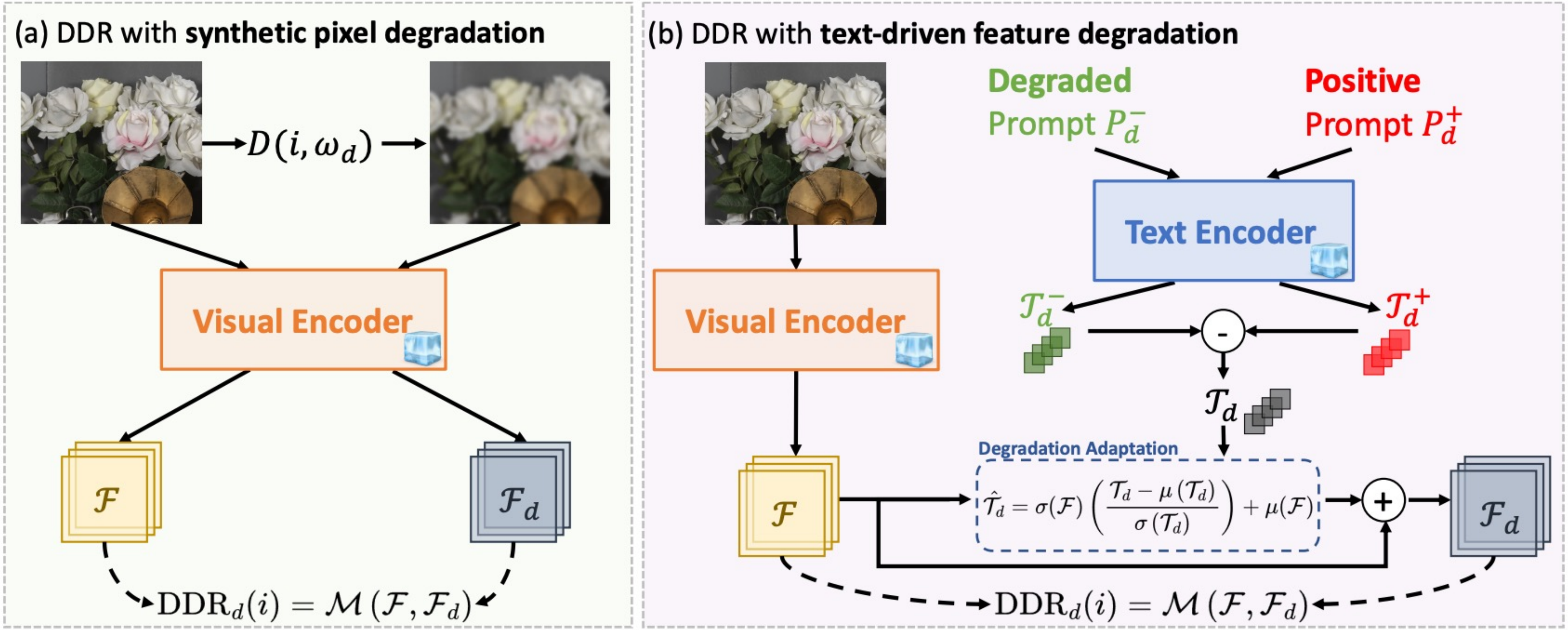
■ Degradation respond of image deep feature:

- ☐ The deep features of images exhibit varying degrees of change when subjecting images to various types of degradation



Contribution

■ Deep Degradation Respond (DDR):



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Contribution

■ DDR as Blind Image Quality Assessment Metric:

$$\mathrm{Q}_{\mathrm{DDR}}(i) = \frac{1}{|\mathcal{D}|} \sum_{d \in \mathcal{D}}^{d} \mathrm{DDR}_d(i)$$

■ DDR as Unsupervised Learning Objective:

$$\min_{\theta} \left(\mathcal{L}_{rec}\left(R_\theta(i), i_{gt}\right) - \lambda_d \sum_{d \in \mathcal{D}}^{d} \mathrm{DDR}_d\left(R_\theta(i)\right) \right)$$

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Experiment

■ **Images with high and low DDR to different degradation types**

(a) Color (b) Noise (c) Blur (d) Exposure

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Experiments

■ Results on opinion-unaware blind image quality assessment (BIQA):

Datasets	NIQE	QAC	PIQE	LPSI	ILNIQE	dipIQ	SNP-NIQE	NPQI	ContentSep	Ours
CSIQ	0.6191	0.4804	0.5120	0.5218	0.8045	0.5191	0.6090	0.6341	0.5871	**0.8289**
LIVE	0.9062	0.8683	0.8398	0.8181	0.8975	**0.9378**	0.9073	0.9108	0.7478	0.8793
TID2013	0.3106	0.3719	0.3636	0.3949	0.4938	0.4377	0.3329	0.2804	0.2530	**0.5844**
KADID	0.3779	0.2394	0.2372	0.1478	0.5406	0.2977	0.3719	0.3909	0.5060	**0.5968**
KonIQ	0.5300	0.3397	0.2452	0.2239	0.5057	0.2375	0.6284	0.6132	0.6401	**0.6455**
LIVEitw	0.4495	0.2258	0.2325	0.0832	0.4393	0.2089	0.4654	0.4752	0.5060	**0.6613**
CID2013	0.6589	0.0299	0.0448	0.3229	0.3062	0.3776	0.7159	0.7698	0.6116	**0.8009**
SPAQ	0.3105	0.4397	0.2317	0.0001	0.6959	0.2189	0.5402	0.5999	0.7084	**0.7249**

a. Quantitative results on OU-BIQA

Experiments

■ Results on image deblurring:

model	loss	GoPro [51] PSNR	GoPro [51] SSIM	RealBlur [52] PSNR	RealBlur [52] SSIM
NAFNet	PSNR	33.1717	0.9482	30.6373	0.9038
	PSNR + LPIPS [3]	33.1660	0.9481	30.7245	0.9044
	PSNR + CTX [2]	32.7879	0.9436	30.4394	0.8985
	PSNR + PDL [7]	32.9417	0.9463	30.6270	0.9039
	PSNR + FDL [8]	32.8321	0.9420	30.1743	0.8864
	PSNR + DDR(ours)	**33.3427**	**0.9500**	**30.7982**	**0.9049**
Restormer	PSNR	33.3398	0.9494	31.9816	0.9098
	PSNR + LPIPS [3]	33.3717	0.9495	31.9639	0.9099
	PSNR + CTX [2]	33.2834	0.9483	31.9893	0.9101
	PSNR + PDL [7]	33.2905	0.9487	31.9900	0.9106
	PSNR + FDL [8]	33.3560	0.9489	31.7673	0.9034
	PSNR + DDR(ours)	**33.4946**	**0.9513**	**32.1759**	**0.9121**

b. Quantitative results on Deblurring

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Experiments

■ Results on image deblurring:

c. Quantitative results on RealBlur dataset.

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