Exploiting Distortion Information for Multi-degraded Image Restoration

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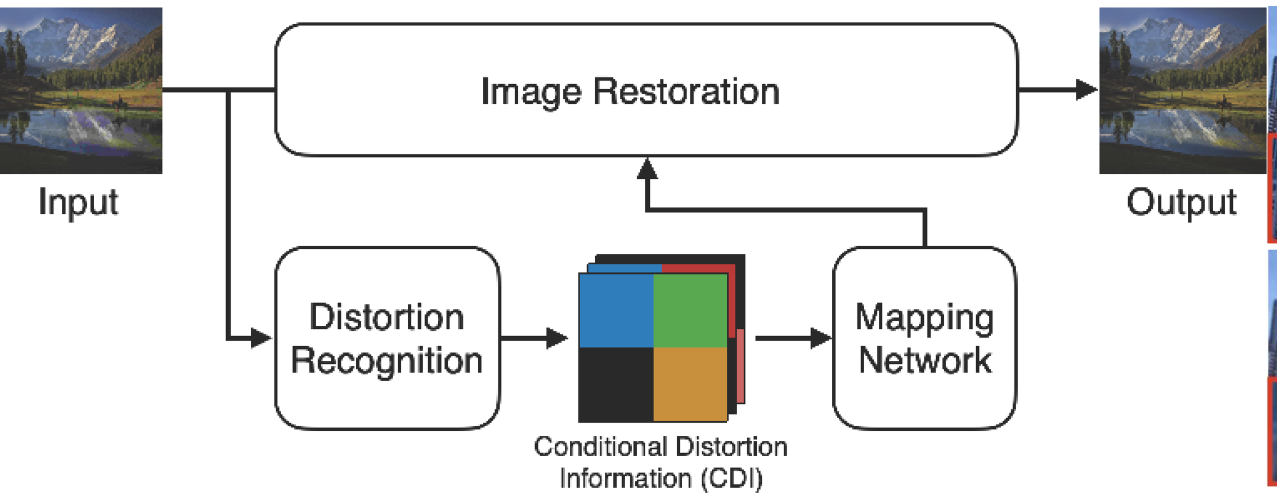
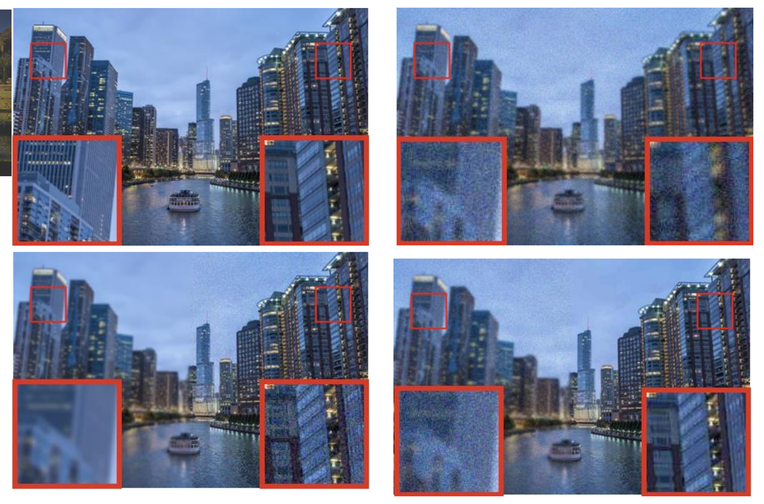
Introduction



Overview of DIGNet



Comparison other multi-distortion

Introduction

- Various types of corruption with unknown strength can be applied in real-world applications
- Previous multi-distortion datasets apply distortion to the entire image, or only a single distortion to each region
- We integrate the idea of two multi-distortion regimes
- To effectively restore the multi-degraded image, we propose a distortion information-guided network (**DIGNet**)

Contribution

- A holistic multi-distortion dataset (**HMDD**) jointly implements the sequentially and spatially-applied corruptions
- In DIGNet, we extract conditional distortion information(**CDI**) that contains useful clues for reconstructing a corrupted image with spatially-variants multi-distortions
- For CDI, we compose two modules; Restoration & Recognition

HMDD

Holistic multi-distortion dataset(HMDD)

- Integrate sequential- and spatial- distortion
- Divide random chunks as $I_{gt} \longrightarrow \{I_{gt}^1, \dots, I_{gt}^k\}$
- Then, corrupt by distortions, widely used in image restoration literature, which are randomly selected parameters

$$D_b(\sigma_b) = \begin{cases} \text{Gaussian blur}(\sigma_b) & \text{if } p_b \geq 0.5 \\ \text{Identity} & \text{if } p_b < 0.5 \end{cases}$$

$$D_n(\sigma_n) = \begin{cases} \text{Gaussian noise}(\sigma_n) & \text{if } p_n \geq 0.5 \\ \text{Identity} & \text{if } p_n < 0.5 \end{cases}$$

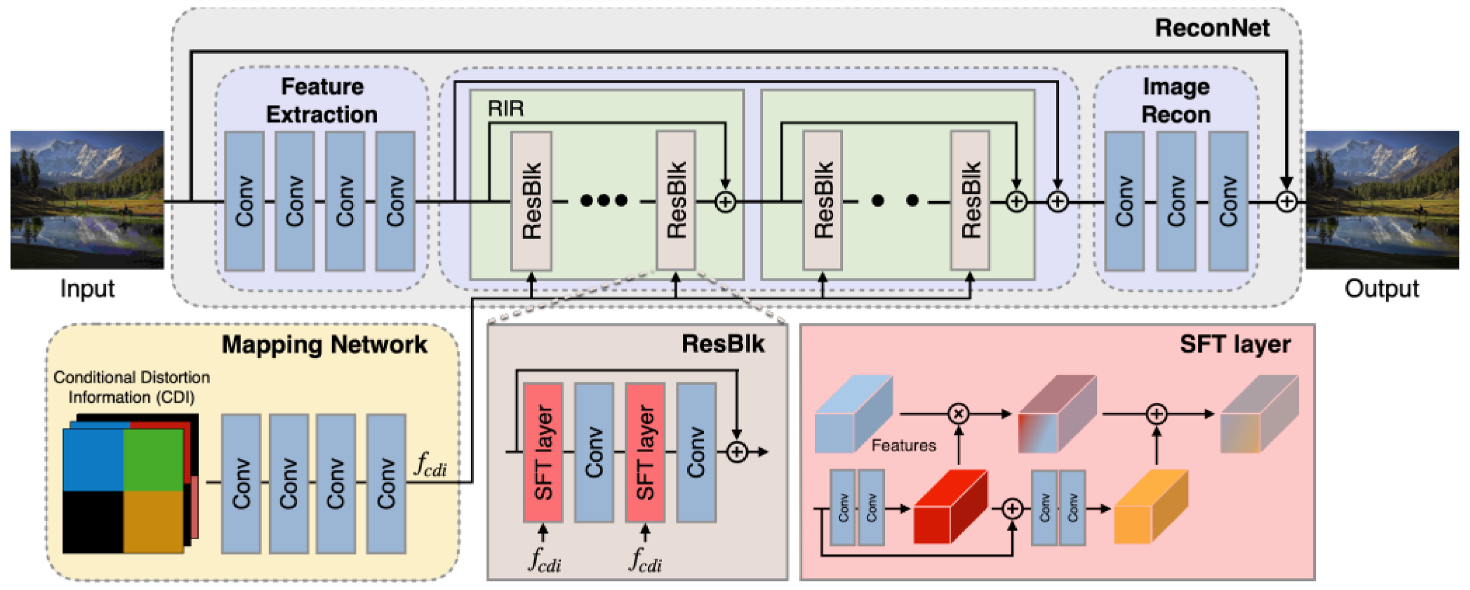
$$D_j(q) = \begin{cases} \text{JPEG compression}(q) & \text{if } p_j \geq 0.5 \\ \text{Identity} & \text{if } p_j < 0.5 \end{cases}$$

(a) $k = 2$ (c) $k = 9$

$$I_d^i = D^i(I_{gt}^i); \quad D^i = D_j^i \circ D_n^i \circ D_b^i$$

$$I_d \longleftarrow \{I_d^1, \dots, I_d^k\}.$$

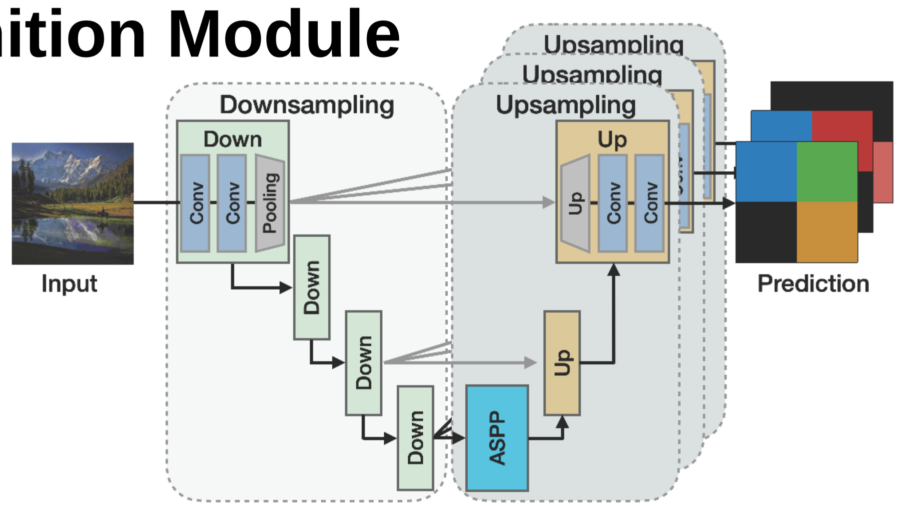
Method



Restoration Module

Method

Recognition Module



- Train the recognition module in a supervised manner by pixel-MSE
- Distortion-wise decoder outputs the distortion-specific representations

Restoration Module

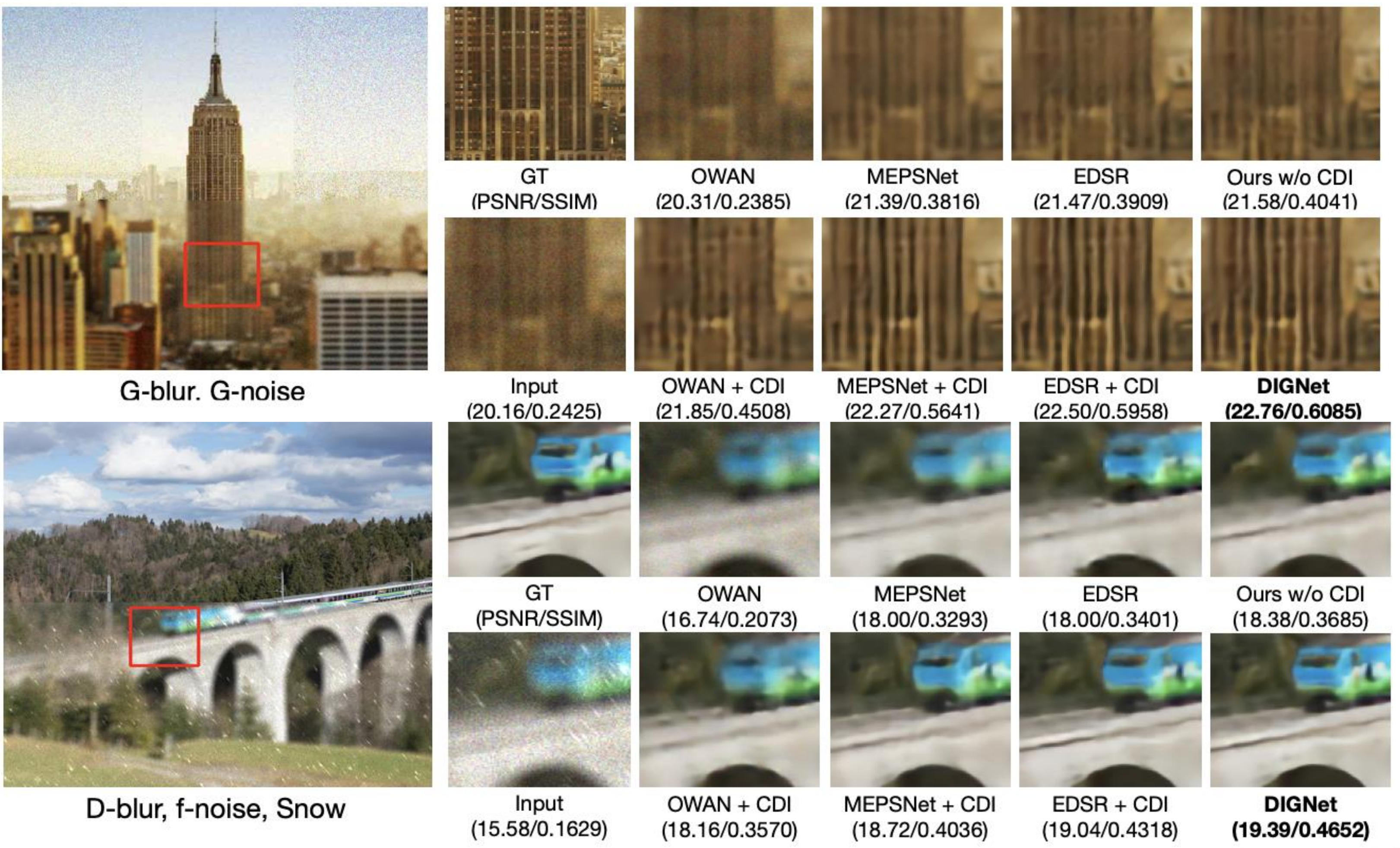
- Mapping network F_{map} embeds to produce features f_cdi as follows: $f_{cdi} = F_{map}(\widehat{M})$
- Spatial feature transform(SFT) are used to convey the distortion information effectively
- The intermediate feature $f_h \in R^{\{C \times W \times H\}}$ is,

$$(\alpha, \beta) = t(f_{cdi}), \qquad SFT(f_h; \alpha, \beta) = \alpha \otimes f_h + \beta,$$

$$f_0 = F_e(x), \qquad f_f = F_f(f_0; \alpha, \beta), \qquad f_o = f_f + f_0,$$

- With image reconstruction F_r, final output is, $\hat{y} = F_r(f_o) + x$

Experimental Results



# Down.	# Up.	ASPP	Accuracy (HMDD) G-blur	G-noise	JPEG	Pixel	→ DIGNet PSNR	SSIM
2	2		60.76	79.22	87.39	44.59	26.60	0.7559
4	2		71.72	84.26	**94.24**	60.29	26.68	0.7594
4	2	✓	**79.12**	**87.93**	94.01	**64.49**	**26.74**	**0.7634**
4	4	✓	78.77	85.38	93.98	63.01	26.71	0.7628

HMDD-r	Accuracy
Snow	88.36
f-noise	97.40
D-blur	81.89
Pixel	67.49

- **Quantitative :** CDI utilization surpasses the other competitors on both dataset
- **Qualitative** : Our method produces the restoration capability regardless of the number of distortions and region

Method	HMDD PSNR	HMDD SSIM	HMDD-r PSNR	HMDD-r SSIM
OWAN [32]	23.52	0.5948	22.25	0.5694
+ CDI	25.96	0.7323	27.13	0.7885
MEPSNet [21]	25.77	0.7257	26.08	0.7757
+ CDI	26.60	0.7606	28.43	0.8270
EDSR [25]	26.25	0.7461	26.70	0.7795
+ CDI	26.63	0.7622	28.56	0.8401
Ours w/o CDI	26.52	0.7528	27.91	0.8177
+ CDI (DIGNet)	**26.74**	**0.7634**	**28.70**	**0.8560**

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