FormResNet: Formatted Residual Learning for Image Restoration

Jianbo Jiao[1], Wei-Chih Tu[2], Shengfeng He[3], Rynson W. H. Lau[1]

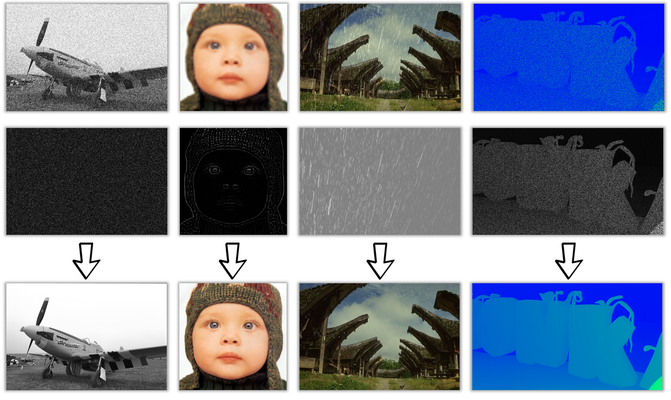
[1]City University of Hong Kong, [2]National Taiwan University, [3]South China University of Technology

IEEE 2017 Conference on Computer Vision and Pattern Recognition

NTIRE CVPR July 21-26 HONOLULU 2017

Problem

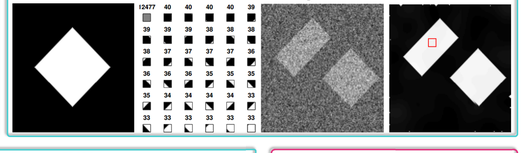
Restore images (natural/depth) from corruptions, and recover more details



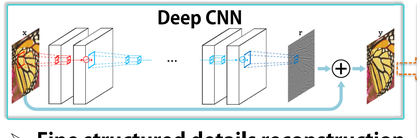
Motivation

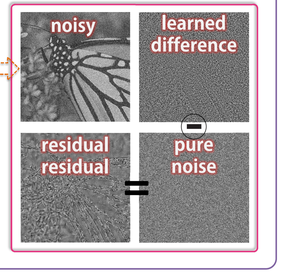
Self similarity

Prior learning



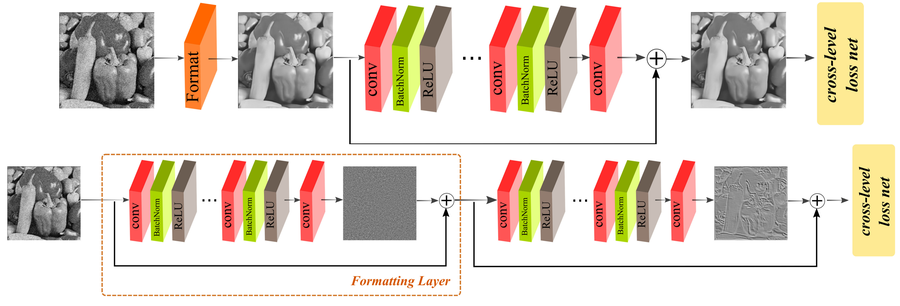
Deep CNN

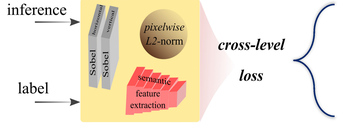




- Fine structured details reconstruction (differentiate from noise)
- MSE-based optimization → blur
- Handle different corruptions independently

Method



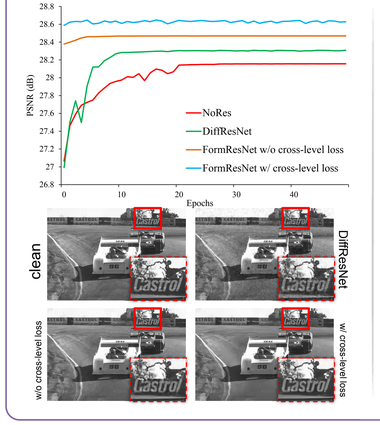


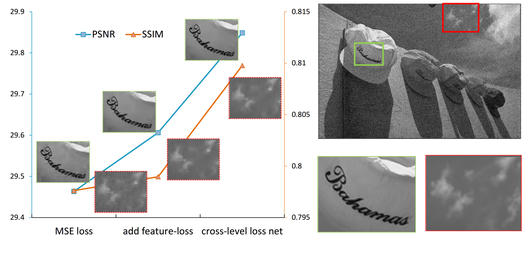
$$L_{pix}(\Theta)=\frac{1}{2N}\sum_{i=1}^{N}\left\|r-R(x^i,\Theta)\right\|^2$$ **Pixel-level MSE**

$$L_{feat}(\Theta)=\frac{1}{2N}\sum_{i=1}^{N}\frac{1}{W_l^i H_l^i C_l^i}\left\|\phi_l(y^i)-\phi_l(\hat{y}^i)\right\|^2$$ **Feature-level loss**

$$L_{grad}(\Theta)=\frac{1}{2N}\sum_{i=1}^{N}\left|\nabla_h(y^i)-\nabla_h(\hat{y}^i)\right|+\left|\nabla_v(y^i)-\nabla_v(\hat{y}^i)\right|$$ **Gradient-domain loss**

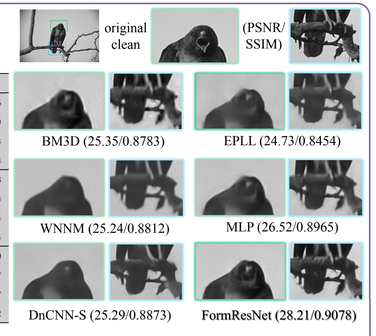
Ablation Studies





Methods	Gaussian 15	Gaussian 25	Gaussian 45	Salt & Pepper	Speckle	Poisson	Average
medfilt2	27.73/0.6987	25.40/0.8745	21.73/0.3515	30.08/0.8682	23.98/0.5184	30.60/0.8745	26.59/0.6976
DnCNN-B* [1]	31.93/0.8624	29.81/0.8037	27.64/0.7297	28.57/0.7876	28.81/0.8087	33.59/0.9019	30.06/0.8156
FormResNet-m	32.61/0.8842	30.34/0.8301	27.82/0.7489	43.76/0.9945	31.01/0.8667	38.80/0.9682	34.06/0.8821

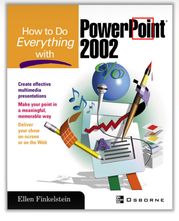
Results

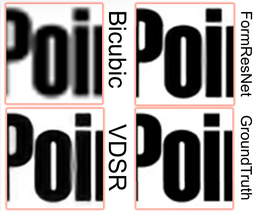


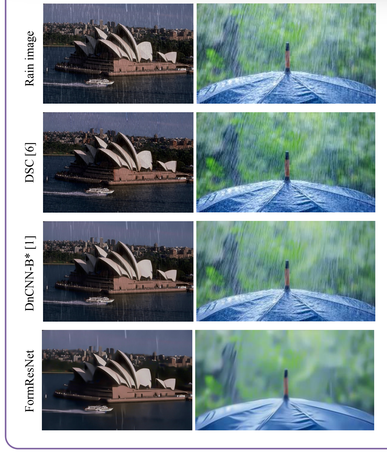
Testsets	σ	BM3D [2]	EPLL [3]	WNNM [4]	MLP [5]	DnCNN-S [1]	FormResNet
Set14	15	32.31/0.8959	32.03/0.8952	32.62/0.8981	-	32.75/0.9034	32.77/0.9036
	25	29.79/0.8471	29.48/0.8436	30.02/0.8506	29.70/0.8455	30.22/0.8584	30.30/0.8599
	45	26.55/0.7663	26.33/0.7556	26.76/0.7693	26.60/0.7603	26.91/0.7747	27.38/0.7873
	75	23.41/0.6766	22.80/0.6443	23.03/0.6622	23.88/0.6829	23.18/0.6637	24.89/0.7093
BSD100	15	30.79/0.8641	30.92/0.8763	31.01/0.8684	-	31.39/0.8831	31.51/0.8848
	25	28.14/0.7842	28.29/0.7979	28.31/0.7893	28.46/0.7960	28.71/0.8106	28.98/0.8153
	45	25.16/0.6680	25.28/0.6743	25.31/0.6707	25.61/0.6656	25.56/0.6883	26.34/0.7114
	75	22.56/0.5703	22.20/0.5481	22.23/0.5446	23.25/0.5771	22.29/0.5515	24.31/0.6154
Kodak	15	32.19/0.8738	32.12/0.8792	32.45/0.8770	-	32.76/0.8883	32.87/0.8890
	25	29.69/0.8112	29.57/0.8134	29.90/0.8145	29.84/0.8142	30.19/0.8300	30.42/0.8307
	45	26.76/0.7207	26.60/0.7148	26.95/0.7220	26.95/0.7129	27.05/0.7329	27.76/0.7457
	75	23.95/0.6413	23.36/0.6126	23.70/0.6295	24.51/0.6461	23.57/0.6273	25.58/0.6702

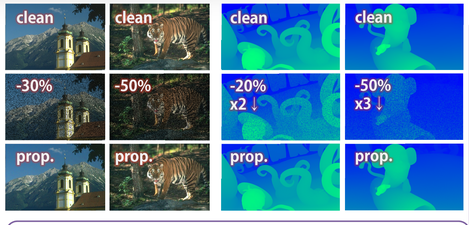
Set5	Scale	Bicubic	VDSR-91	VDSR-291	FormResNet-91
	x2	33.66	37.06	37.53	**37.55**
	x3	30.39	33.27	33.66	**33.75**
	x4	28.42	30.95	31.35	**31.40**

Set14*	Scale	Bicubic	VDSR-291	FormResNet-91
	x2	30.24/0.8688	33.03/0.9124	**33.09/0.9127**
	x3	27.55/0.7742	29.77/0.8314	**29.84/0.8321**
	x4	26.00/0.7027	28.01/0.7674	**28.07/0.7682**









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