Patch-Craft Self-Supervised Training for Correlated Image Denoising

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Patch-Craft Training – Problem Definition

Self-supervised training for image denoising

- Noise can have non-Gaussian distribution
- Noise can exhibit short-range spatial and cross-channel correlations
- Capturing corrupted images is relatively straightforward
- Obtaining ground-truth or estimating noise model is difficult
- In RGB space real sensor noise typically correlated

Patch-Craft Training – Sample Results

Clean

Noisy

N2N, 24.27dB

R2R, 25.26dB

BM3D-O, 24.22dB

PC-DnCNN (ours), 28.03 dB

Patch-Craft Training – Overview

Noisy images
$\{\mathbf{y}_1, \dots, \mathbf{y}_M\}$

$\{\mathbf{y}_1, \dots, \mathbf{y}_M\} \backslash \mathbf{y}_{M/2}$

$\mathbf{y}_{M/2}$

Patch Matching

$\mathbf{y}_{M/2}$

Patch-craft image

$\tilde{\mathbf{x}}_{M/2}$

$\mathbf{y}_{M/2}$

Denoiser
$F(\mathbf{y})$

$F(\mathbf{y}_{M/2})$

Loss
$\tilde{l} = \|F(\mathbf{y}) - \tilde{\mathbf{x}}\|_2^2$

Lemma

Lemma:

If $\mathbf{w}$ is statistically independent of $\mathbf{x}$ and $\mathbf{z}$, and admits a zero mean $\mathbb{E}[\mathbf{w}] = \mathbf{0}$, then

$$\mathbb{E}\left[\nabla\tilde{l}\,\right] = \mathbb{E}[\nabla\|F(\mathbf{y}) - \tilde{\mathbf{x}}\|_2^2] = \nabla(\mathbb{E}\|F(\mathbf{y}) - \mathbf{x}\|_2^2\,)$$

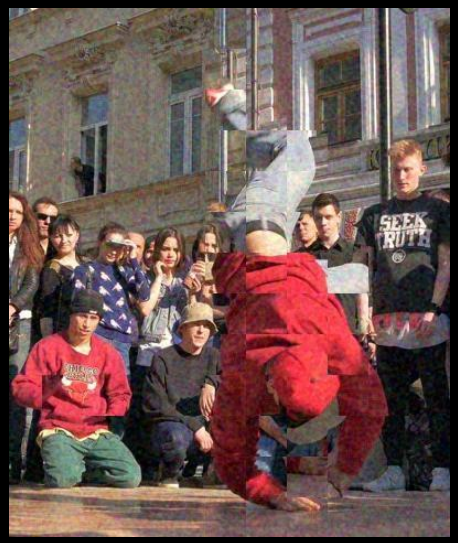
Conclusion:

Training with the loss $\tilde{l}$ is equivalent to SGD with clean targets $\mathbf{x}$

Correlation Reduction – Definitions

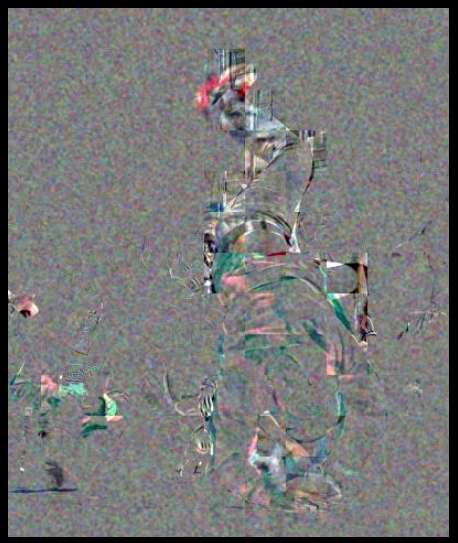
$\mathbf{y}$

$-$



$\tilde{\mathbf{x}}$

$=$



$\mathbf{r}$

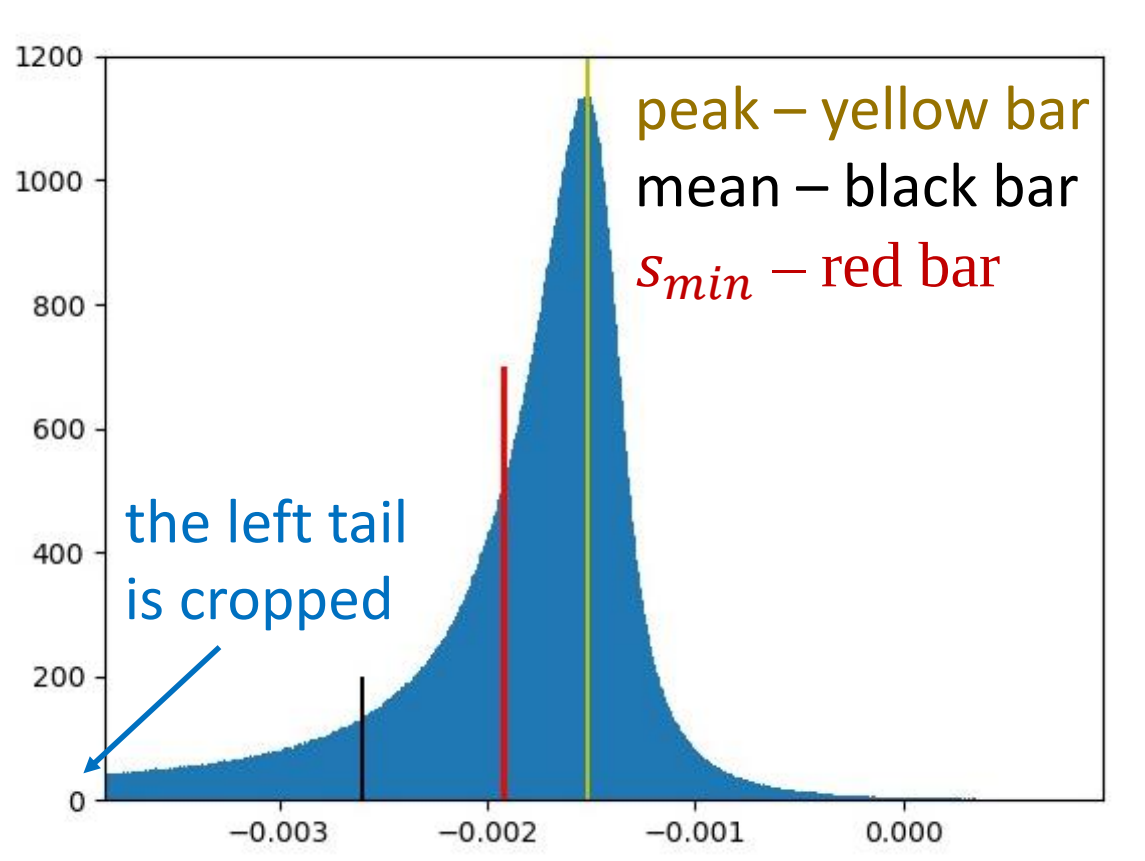
$$s_{y,r} = \sum_{i,j} (y_{i,j} - \bar{y})(r_{i,j} - \bar{r})$$

empirical covariance between $\mathbf{y}$ and $\mathbf{r}$

We are going to use the histogram of $s_{y,r}$

Correlation Reduction

$s_{y,r}$ histogram



Algorithm:

- Exclude from the training set all image pairs for which $s_{yr} < s_{min}$

  cut the left tail

- The mean of the resulting histogram coincides with its peak

Results – Correlated Gaussian Noise

σ	k	Noisy	B2U	N2N	R2R	BM3D-O	PC-DnCNN (ours)
10	3	28.13	23.85	28.85	32.50	33.56	35.32
	4	28.13	23.45	28.67	31.21	32.30	34.79
15	3	24.61	24.44	25.43	29.59	31.11	33.16
	4	24.61	22.26	25.26	28.26	29.79	32.57
20	3	22.11	7.74	23.02	27.57	29.49	31.63
	4	22.11	22.33	22.91	25.93	28.15	30.97
Average		24.95	20.68	25.69	29.18	30.73	33.07

Results – Real-World Image Noise

ISO	Noisy	B2U	N2N	R2R	BM3D-O	PC-DnCNN (ours)
1600	37.67	36.88	37.71	39.58	41.12	41.33
3200	35.03	4.94	35.10	37.18	38.99	39.64
6400	32.10	4.98	32.19	34.67	36.57	37.32
12800	29.25	23.79	29.33	31.71	34.30	35.15
25600	25.77	20.11	25.86	28.26	31.35	32.38
Average	31.96	18.14	32.04	34.28	36.47	37.16

Results – Correlated Gaussian Noise

Clean

Noisy

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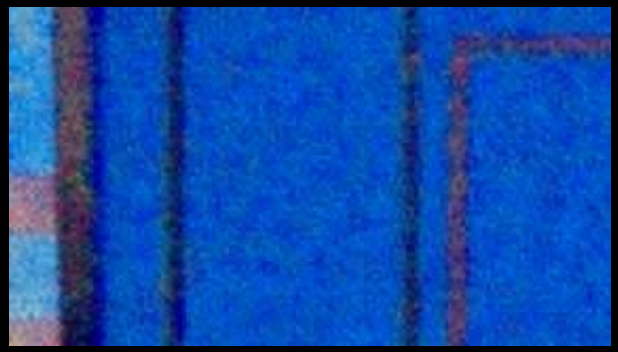
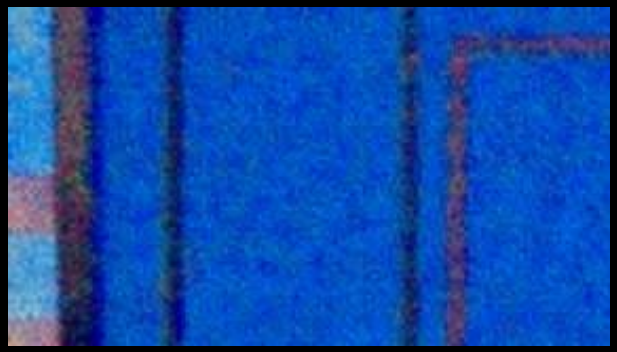
PC-DnCNN (ours), 28.03 dB

Results – Real-World Noise

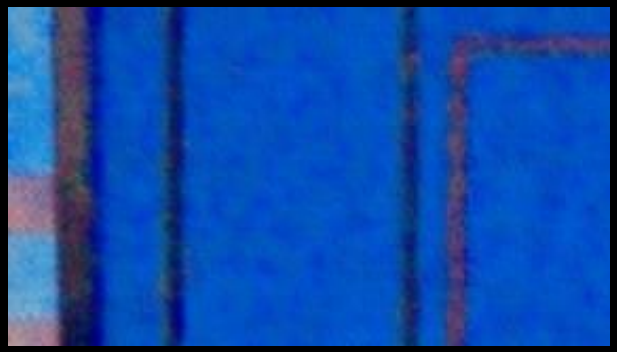
Clean



Noisy, 28.29 dB



N2N, 28.36 dB



R2R, 31.62 dB

BM3D-O, 33.60 dB

PC-DnCNN (ours), 34.41 dB

Patch-Craft Denoising – Summary

- Novel self-supervised framework for correlated image denoising
- Relies on availability of short video sequences
- Applies patch matching for building patch-craft images
- Excludes images with high correlation from the training set
- Achieves an outstanding denoising performance compared with the recent state-of-the-art self-supervised methods