Supplementary Material:

Loss-Specific Training of Non-Parametric Image Restoration Models: A New State of the Art

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Abstract. This supplementary document contains results that were omitted from the main paper due to a lack of space. In particular, we provide a closer look at the denoising quality of our method, as well as several exemplary predictions by all of our systems and its competitors, on the following tasks:

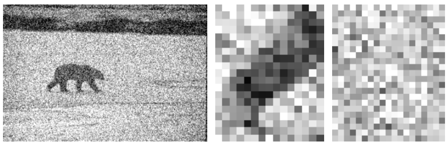
1. denoising (at all noise levels);
2. JPEG deblocking (at all quality settings);
3. structured noise/dust artefacts (small and large).

1 Denoising results

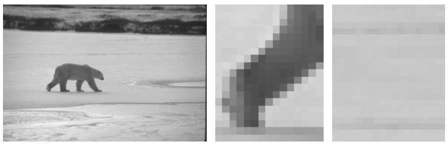
We compare Field-of-Experts (FoE) [1], BM3D [2], LSSC [3] and EPLL [4] to our method.

1.1 Zoom-In

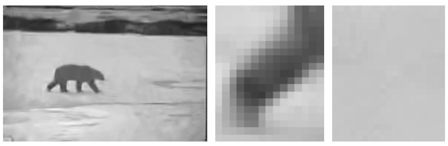
We first take a closer look at one particular image from the test set and compare zoom-ins of the predictions by several systems.



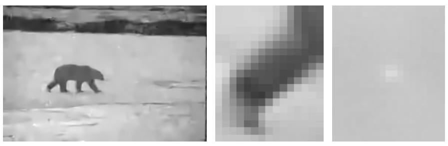
Noisy input



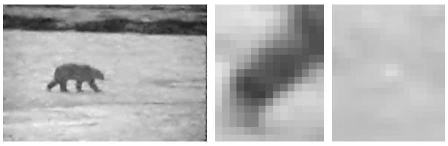
Ground truth



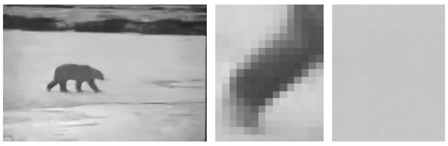
BM3D



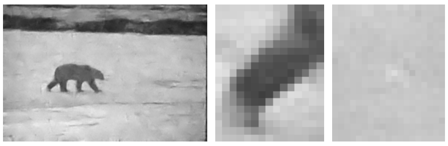
EPLL



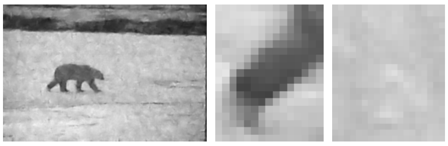
FoE



PsnrRTF$_{\text{All}}$



PsnrRTF$_{\text{Plain}}$



NlplRTF$_{\text{Plain}}$

We next show an exhaustive set of predictions of all system configurations on three images from the test set.

1.2 Results at $\boldsymbol{\sigma = 20}$

Ground truth

Noisy input

FoE

BM3D

LSSC

EPLL

PsnrRTF$_{\text{Plain}}$

PsnrRTF$_{\text{Bm3d}}$

PsnrRTF$_{\text{All}}$

MaeRTF$_{\text{Plain}}$

MaeRTF$_{\text{Bm3d}}$

MaeRTF$_{\text{All}}$

SsimRTF$_{\text{Plain}}$

SsimRTF$_{\text{Bm3d}}$

SsimRTF$_{\text{All}}$

NlplRTF$_{\text{Plain}}$

NlplRTF$_{\text{Bm3d}}$

NlplRTF$_{\text{All}}$

1.3 Results at $\sigma = 30$

Ground truth

Noisy input

FoE

BM3D

LSSC

EPLL

$\text{PsnrRTF}_{\text{Plain}}$

$\text{PsnrRTF}_{\text{BM3D}}$

$\text{PsnrRTF}_{\text{All}}$

$\text{MaeRTF}_{\text{Plain}}$

MaeRTF$_{\text{Bm3d}}$

MaeRTF$_{\text{All}}$

SsimRTF$_{\text{Plain}}$

SsimRTF$_{\text{Bm3d}}$

SsimRTF$_{\text{All}}$

NlplRTF$_{\text{Plain}}$

NlplRTF$_{\text{Bm3d}}$

NlplRTF$_{\text{All}}$

1.4 Results at $\sigma = 40$

Ground truth

Noisy input

FoE

BM3D

LSSC

EPLL

PsnrRTF$_{\text{Plain}}$

PsnrRTF$_{\text{BM3D}}$

PsnrRTF$_{\text{All}}$

MaeRTF$_{\text{Plain}}$

MaeRTF$_{\text{Bm3d}}$

MaeRTF$_{\text{All}}$

SsimRTF$_{\text{Plain}}$

SsimRTF$_{\text{Bm3d}}$

SsimRTF$_{\text{All}}$

NlplRTF$_{\text{Plain}}$

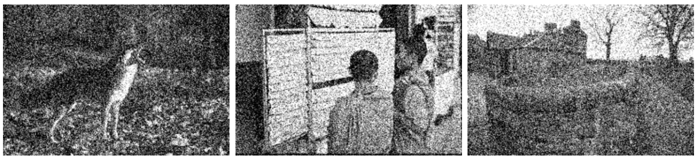
NLPLRTF$_{\text{BM3D}}$

NLPLRTF$_{\text{ALL}}$

1.5 Results at $\sigma = 50$

Ground truth

Noisy input



FoE

BM3D

LSSC

EPLL

PsnrRTF$_{\text{Plain}}$

PsnrRTF$_{\text{Bm3d}}$

PsnrRTF$_{\text{All}}$

MaeRTF$_{\text{Plain}}$

MaeRTF$_{\text{Bm3d}}$

MaeRTF$_{\text{All}}$

SsimRTF$_{\text{Plain}}$

SsimRTF$_{\mathrm{BM3D}}$

SsimRTF$_{\mathrm{ALL}}$

NlplRTF$_{\mathrm{PLAIN}}$

NlplRTF$_{\mathrm{BM3D}}$

NlplRTF$_{\mathrm{ALL}}$

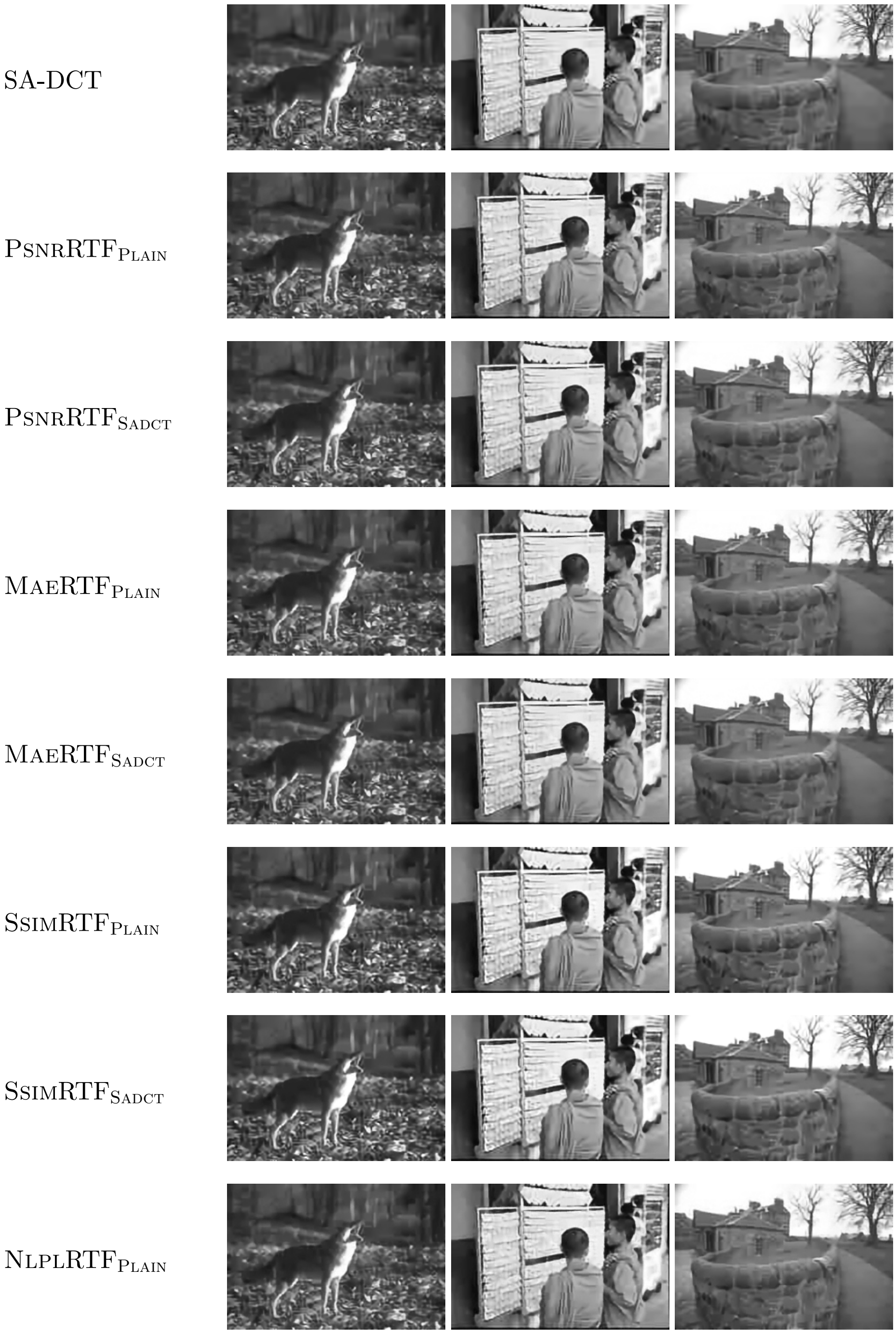
2 JPEG deblocking results

We compare SA-DCT [5] to all configurations of our system.

2.1 Results at quality 10

Ground truth

Lossy input


SA-DCT
PsnrRTF$_{\text{Plain}}$
PsnrRTF$_{\text{Sadct}}$
MaeRTF$_{\text{Plain}}$
MaeRTF$_{\text{Sadct}}$
SsimRTF$_{\text{Plain}}$
SsimRTF$_{\text{Sadct}}$
NlplRTF$_{\text{Plain}}$

NlplRTF$_{\mathrm{Sadct}}$

2.2 Results at quality 20

Ground truth

Lossy input

SA-DCT

PsnrRTF$_{\mathrm{Plain}}$

PsnrRTF$_{\mathrm{Sadct}}$

MaeRTF$_{\mathrm{Plain}}$

MaeRTF$_{\text{Sadct}}$

SsimRTF$_{\text{Plain}}$

SsimRTF$_{\text{Sadct}}$

NlplRTF$_{\text{Plain}}$

NlplRTF$_{\text{Sadct}}$

2.3 Results at quality 30

Ground truth

Lossy input

SA-DCT

PsnrRTF$_{\text{Plain}}$

PsnrRTF$_{\text{SaDCT}}$

MaeRTF$_{\text{Plain}}$

MaeRTF$_{\text{SaDCT}}$

SsimRTF$_{\text{Plain}}$

SsimRTF$_{\text{SaDCT}}$

NlplRTF$_{\text{Plain}}$

NlplRTF$_{\mathrm{Sadct}}$

2.4 Results at quality 40

Ground truth

Lossy input

SA-DCT

PsnrRTF$_{\mathrm{Plain}}$

PsnrRTF$_{\mathrm{Sadct}}$

MaeRTF$_{\mathrm{Plain}}$

$\text{MaeRTF}_{\text{Sadct}}$

$\text{SsimRTF}_{\text{Plain}}$

$\text{SsimRTF}_{\text{Sadct}}$

$\text{NlplRTF}_{\text{Plain}}$

$\text{NlplRTF}_{\text{Sadct}}$

3 Results on the structured noise dataset

None of the other denoising methods described in this paper can handle the structured noise present in the corrupted images. To illustrate this point, we show the results achieved by BM3D [2]. When running BM3D, for each image, we estimate the variance of the noise from the ground truth and the noisy input image to give the method a fair chance. However, the additive white Gaussian noise assumption is severly violated on this dataset, so BM3D fails to recover the regions covered by “dust”. Moreover, it blurs the “good” regions .

In contrast, our system is highly capable of recovering the regions that were corrupted by dust.

3.1 Results at dust size 5

Ground truth

Noisy input

BM3D

MseRTF$_{\text{Plain}}$

IssimRTF$_{\text{Plain}}$

3.2 Results at dust size 10

Ground truth

Noisy input

BM3D

$\textsc{MseRTF}_{\textsc{Plain}}$

$\textsc{IssimRTF}_{\textsc{Plain}}$

References

1. Schmidt, U., Gao, Q., Roth, S.: A generative perspective on MRFs in low-level vision. In: CVPR. (2010)
2. Dabov, K., Foi, A., Katkovnik, V., Egiazarian, K.O.: Image denoising by sparse 3-D transform-domain collaborative filtering. IEEE Transactions on Image Processing **16** (2007) 2080–2095
3. Mairal, J., Bach, F., Ponce, J., Shapiro, G., Zisserman, A.: Non-local sparse models for image restoration. In: ICCV. (2009)
4. Zoran, D., Weiss, Y.: From learning models of natural image patches to whole image restoration. In: ICCV. (2011)
5. Foi, A., Katkovnik, V., Egiazarian, K.: Pointwise shape-adaptive DCT for high-quality denoising and deblocking of grayscale and color images. IEEE Transactions on Image Processing **16** (2007) 1395–1411