Supplementary Material for “Outlier-Aware Post-Training Quantization for Image Super-Resolution”

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1. PTQ for SRResNet

We further extend the comparison with PTQ methods using the SRResNet network. The results, presented in Table 1, show that our method consistently achieves the best performance across all datasets and settings.

Method	FT	W / A	Set5		Set14		BSD100		Urban100	
			PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
SRResNet [4]	-	32/32	32.06	0.892	28.50	0.779	27.52	0.735	25.86	0.779
SRResNet-MSE [1]	×	6 / 6	31.40	0.885	27.93	0.770	27.07	0.727	25.40	0.766
SRResNet-MinMax [3]	×	6 / 6	31.75	0.883	28.27	0.769	27.32	0.726	25.59	0.765
SRResNet-Percentile [5]	×	6 / 6	19.60	0.803	19.07	0.693	20.30	0.676	17.40	0.682
SRResNet-PTQ4SR [6]	✓	6 / 6	31.79	0.885	28.35	0.773	27.40	0.729	25.66	0.768
SRResNet-AdaBM [2]	✓	6 / 6	31.79	0.885	28.37	0.773	27.41	0.729	25.68	0.769
SRResNet-Ours	✓	6 / 6	**31.91**	**0.888**	**28.42**	**0.775**	**27.45**	**0.731**	**25.71**	**0.772**
SRResNet-MSE [1]	×	4 / 4	25.07	0.820	23.99	0.704	24.10	0.669	21.42	0.681
SRResNet-MinMax [3]	×	4 / 4	28.78	0.819	26.51	0.708	26.09	0.666	23.77	0.679
SRResNet-Percentile [5]	×	4 / 4	19.47	0.774	19.03	0.662	20.19	0.642	17.28	0.637
SRResNet-PTQ4SR [6]	✓	4 / 4	31.08	0.868	27.96	0.757	27.06	0.711	25.06	0.739
SRResNet-AdaBM [2]	✓	4 / 4	31.43	0.877	28.04	0.763	27.16	0.718	25.24	0.749
SRResNet-Ours	✓	4 / 4	**31.47**	**0.880**	**28.16**	**0.767**	**27.25**	**0.722**	**25.33**	**0.754**

Table 1. Performance comparison between PTQ methods using SRResNet, with a scale factor of 4.

2. Additional qualitative results

We provide additional visual comparisons of PTQ methods using EDSR and SRResNet networks in Figures 1 and 2. The results demonstrate that our method achieves performance comparable to that of a full-precision model. For EDSR, as shown in Figure 1, our method effectively preserves details while maintaining robustness to noise. For SRResNet, as illustrated in Figure 2, both PTQ4SR [6] and AdaBM [2] introduce noticeable noise, particularly on regions such as the white wall in the first row. In contrast, our method effectively suppresses noise while maintaining high visual fidelity.

References

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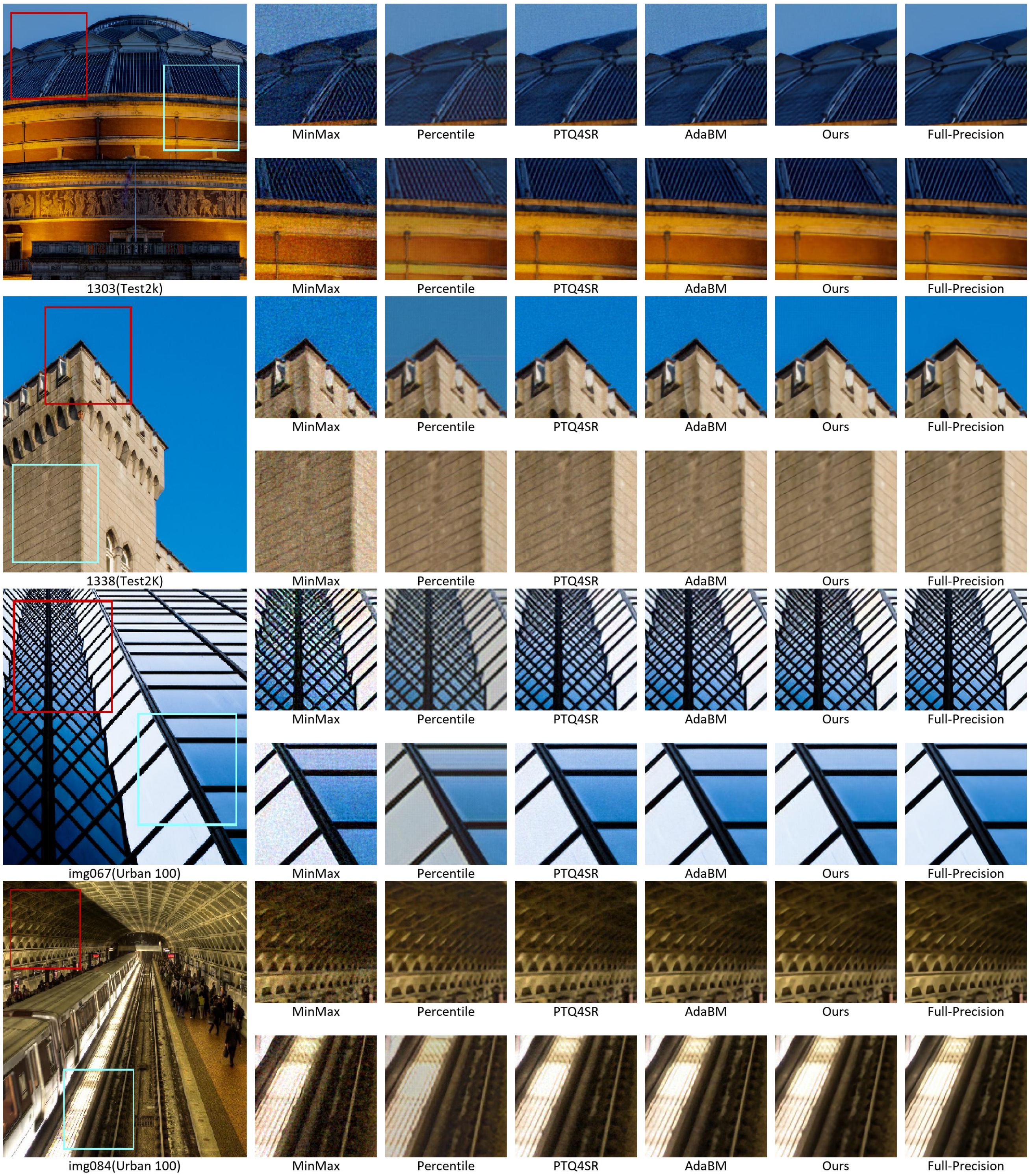

Figure 1. Visual comparison between different PTQ methods with the EDSR network under W4A4 setting.

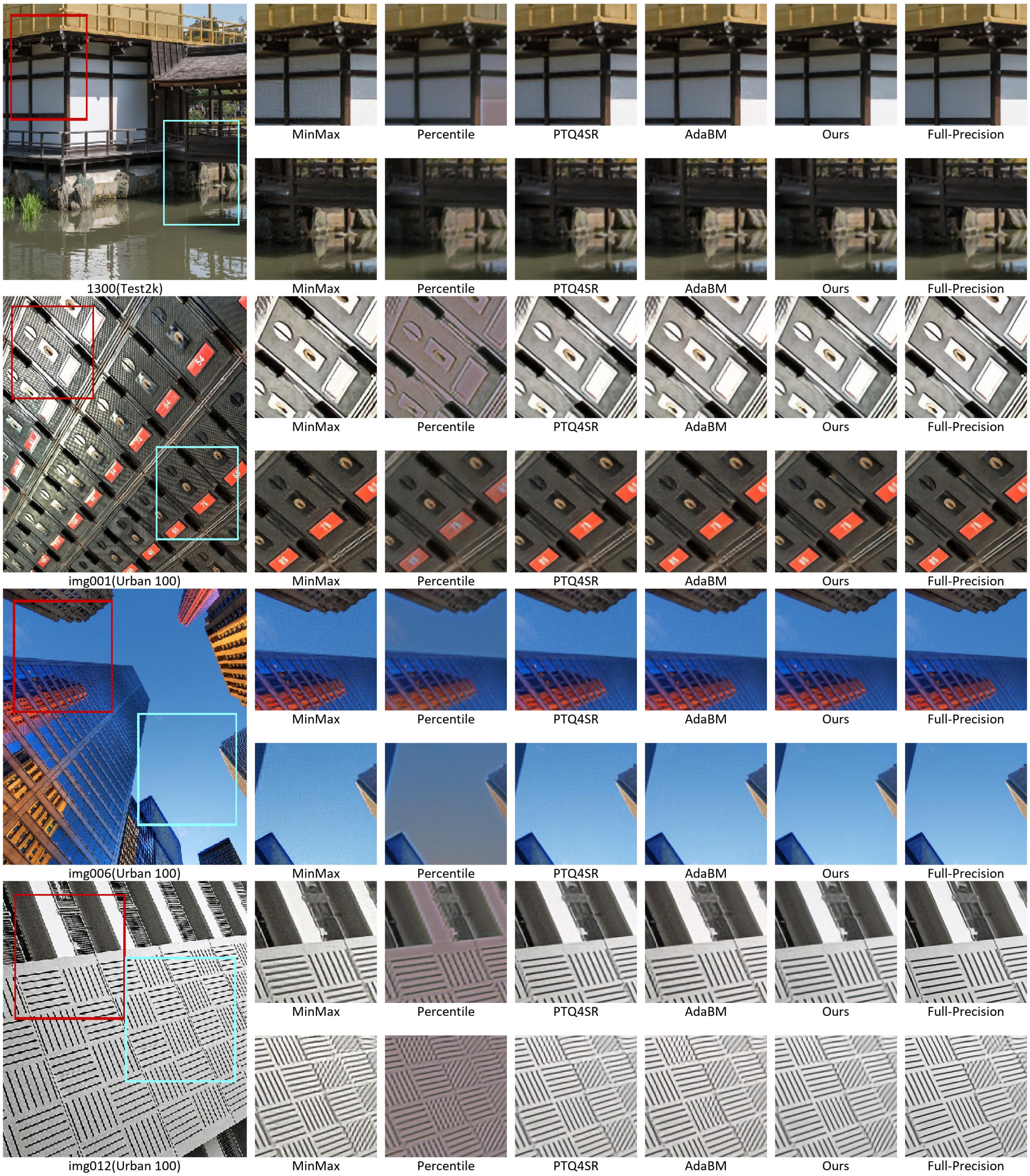

Figure 2. Visual comparison between different PTQ methods with the SRResNet network under W4A4 setting.