Enhancing Quality of Compressed Images by Mitigating Enhancement Bias Towards Compression Domain

Supplementary Material

Meth.	Data.	Raw	Enh.	Δ to raw	Comp.	Δ to raw
[14]	DIV2K	0.51	0.49	**-0.02**	0.67	**+0.16**
	Flickr2K	0.51	0.49	**-0.02**	0.66	**+0.15**
[15]	DIV2K	0.66	0.33	**-0.33**	0.71	**+0.05**
	Flickr2K	0.62	0.31	**-0.31**	0.64	**+0.02**

Table 1. Discriminator-evaluated realism scores for raw, enhanced, and compressed images. Higher scores indicate greater perceived realism. The results reveal that existing methods regard compressed images as more realistic than raw images.

1. Further Analysis of Enhancement Bias Towards Compression Domain

In the main paper, our findings for BPG-compressed images with QP set to 37 highlighted the prevalent enhancement bias towards the compression domain. To extend this investigation, this section presents analogous observations for JPEG-compressed images with a QF of 30, considering the widespread use of both BPG and JPEG codecs in image compression.

As delineated in Tab. 1, while discriminators effectively differentiate between enhanced and raw images, assigning higher realism scores to the latter, a notable difficulty arises in distinguishing compressed images from raw ones. More strikingly, compressed images receive higher realism scores than their raw counterparts. This trend signifies a perceived realism in the compression domain, thereby inadvertently contributing to the enhancement bias towards this domain.

Fig. 1 illustrates a consistent pattern where the enhancement domain more closely aligns with the compression domain rather than the raw domain. Horizontal deviations, ranging from -2.52% to -26.03%, further corroborate the widespread bias towards the compression domain across various datasets and metrics.

2. Extended Results of Objective Quality Evaluation

The main paper detailed the objective quality results of enhanced BPG-compressed images with QP set to 37. We now present, in Tabs. 2 to 5, the objective quality for other QP settings and JPEG-compressed images. Consistently, our method shows enhancement over perception-driven SR baselines [14, 15] across all evaluated metrics. Despite these baselines outperforming traditional fidelity-oriented methods in most aspects, they generally lag in PSNR, a metric not entirely aligned with perceptual quality as noted by [1]. However, our method successfully boosts the PSNR performance of these baselines, marking a significant advancement in the field of perception-driven quality enhancement. In essence, our approach not only achieves state-of-the-art performance in perceptual quality enhancement of compressed images but also substantially improves fidelity as achieved by SR baseline methods.

3. Additional Evaluation of Rate-Distortion Performance

Building on the main paper's rate-distortion performance analysis using FID and LPIPS, Fig. 2 extends this evaluation to additional metrics for both BPG-compressed and JPEG-compressed images. Our method's rate-distortion curves consistently outperform those of the compared methods, underscoring superior image quality enhancement across various codecs and bitrates.

Additionally, we assess the rate-distortion performance using the BD-BR metric for JPEG-compressed images, supplementing the BPG-focused analysis in the main paper. As depicted in Tab. 6, our approach achieves significant bitrate reductions while preserving perceptual quality, evident in the minimal BD-BR values. Notably, even when considering PSNR, our method records a baseline performance enhancement of at least 2.73%. Overall, this comprehensive analysis affirms our method's advancement in both rate-perception and rate-fidelity performance.

4. Additional Visual Demonstrations

To further illustrate the impact of our method in mitigating enhancement bias, Figs. 3 and 4 provide additional visual demonstrations. Compared methods often exhibit a stronger resemblance of enhanced images to their compressed counterparts, as evidenced by weaker residuals. In contrast, our method distinctly generates images with more vivid details, closely mirroring the residuals of raw images.

References

[1] Yochai Blau and Tomer Michaeli. The perception-distortion tradeoff. In *2018 IEEE/CVF conference on computer vision and pattern recognition*. IEEE, 2018. 1

[2] Yochai Blau, Roey Mechrez, Radu Timofte, Tomer Michaeli, and Lihi Zelnik-Manor. The 2018 PIRM Challenge on Perceptual Image Super-Resolution. In *Proceedings of the Eu-*

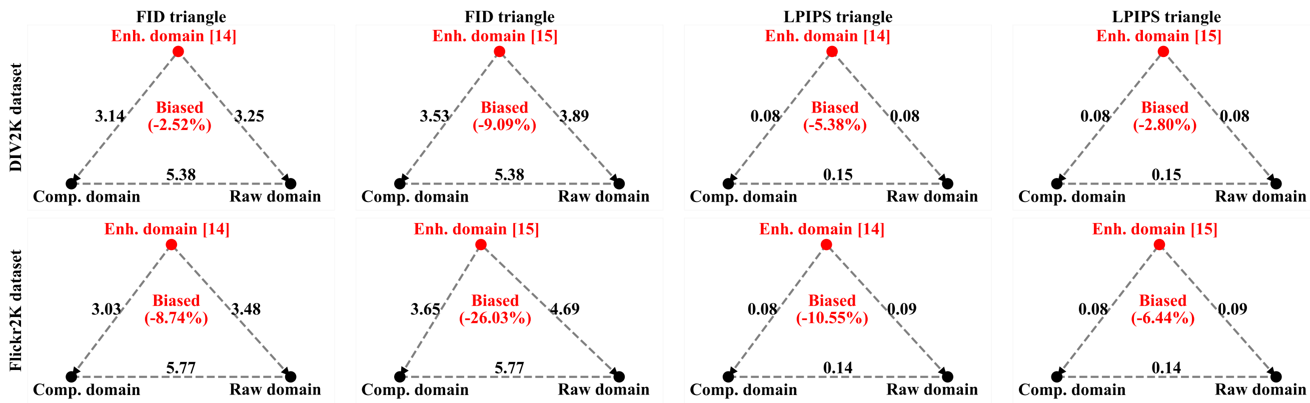

Figure 1. Similarity scores between compression, raw, and enhancement domains. Lower FID and LPIPS scores indicate greater similarity. The horizontal deviation of each vertex relative to the centroid of its base, calculated with float precision on original data, is also shown. The results underscore the enhancement bias, demonstrating a closer alignment of the enhancement domain with the compression domain than with the raw domain.

QP	Metric	Comp.	[5]	[13]	[18]	[6]	[20]	[16]	[17]	[14]	[15]	Ours w/ [14]	Ours w/ [15]
27	↑ AHIQ [9]	.513	.529	.534	.533	.534	.530	.532	.534	.510	.518	.525	**.535**
	↑ CLIP. [12]	.620	.647	.646	.645	.648	.645	.646	.644	.661	.658	**.670**	.668
	↓ DISTS [4]	.058	.060	.066	.066	.065	.066	.066	.065	.026	.025	.024	**.024**
	↓ FID [7]	1.68	1.69	1.71	1.76	1.84	1.76	1.81	1.78	2.02	2.15	**1.67**	1.90
	↑ Hyper. [11]	.556	.576	.596	.600	.602	.594	.598	.601	.568	.581	.586	**.602**
	↓ LPIPS [19]	.094	.094	.093	.093	.090	.093	.092	.091	.049	.045	.045	**.043**
	↑ MUSIQ [8]	66.2	66.7	67.1	67.1	**67.1**	67.0	67.0	67.0	65.0	65.6	65.6	66.3
	↓ NIQE [10]	3.40	3.58	3.64	3.65	3.63	3.65	3.64	3.64	3.00	3.09	**2.90**	2.91
	↓ PI [2]	3.63	3.76	3.83	3.81	3.80	3.81	3.81	3.91	3.21	3.30	**3.15**	3.18
	↑ PSNR (dB)	35.9	36.5	36.7	36.8	**37.0**	36.8	36.9	37.0	34.1	34.8	34.7	35.5
	↑ TOPIQ [3]	.917	.918	.918	.918	.920	.918	.919	.920	.928	.929	.931	**.931**
32	↑ AHIQ [9]	.482	.495	.503	.501	.504	.502	.503	.503	.489	.491	.502	**.509**
	↑ CLIP. [12]	.571	.606	.609	.610	.618	.608	.611	.611	.666	.656	**.674**	.668
	↓ DISTS [4]	.089	.095	.102	.102	.100	.103	.102	.101	.041	.042	**.038**	.039
	↓ FID [7]	4.51	4.66	4.68	4.77	4.86	4.78	4.72	4.73	4.36	5.63	**3.87**	4.19
	↑ Hyper. [11]	.515	.553	.577	.581	.588	.582	.581	.583	.566	.573	.584	**.594**
	↓ LPIPS [19]	.149	.146	.146	.145	.141	.145	.143	.142	.078	.077	.073	**.073**
	↑ MUSIQ [8]	64.7	65.4	66.0	66.1	66.2	66.0	66.1	66.1	65.4	65.6	65.9	**66.5**
	↓ NIQE [10]	3.75	4.00	4.10	4.08	4.08	4.11	4.10	4.08	2.94	3.11	**2.83**	2.89
	↓ PI [2]	3.94	4.12	4.19	4.17	4.18	4.19	4.18	4.27	3.19	3.36	**3.13**	3.19
	↑ PSNR (dB)	33.3	33.8	34.0	34.1	**34.3**	34.1	34.2	34.2	31.7	32.3	32.2	33.2
	↑ TOPIQ [3]	.859	.856	.855	.855	.860	.854	.857	.860	.894	.896	**.902**	.901

Table 2. Objective quality of enhanced BPG-compressed images with QP set to 27 and 32. All results are to three significant figures.

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[5] Chao Dong, Yubin Deng, Chen Change Loy, and Xiaoou Tang. Compression artifacts reduction by a deep convolutional network. In *2015 IEEE international conference on computer vision (ICCV)*. IEEE, 2015. 2, 3, 4

[6] Shi Guo, Zifei Yan, Kai Zhang, Wangmeng Zuo, and Lei Zhang. Toward convolutional blind denoising of real pho-

QP	Metric	Comp.	[5]	[13]	[18]	[6]	[20]	[16]	[17]	[14]	[15]	Ours w/ [14]	Ours w/ [15]
	↑ AHIQ [9]	.371	.370	.372	.375	.384	.375	.381	.380	.394	.401	.414	**.425**
	↑ CLIP. [12]	.397	.441	.464	.471	.515	.479	.487	.490	.651	.631	**.660**	.645
	↓ DISTS [4]	.170	.179	.186	.186	.183	.188	.186	.185	.088	.098	**.083**	.092
	↓ FID [7]	20.7	22.2	22.7	23.3	24.0	23.1	23.2	23.1	15.7	21.0	**15.1**	17.5
	↑ Hyper. [11]	.379	.451	.484	.492	.518	.492	.494	.500	.548	.545	**.572**	.568
42	↓ LPIPS [19]	.313	.304	.302	.300	.292	.302	.297	.294	.194	.181	.180	**.174**
	↑ MUSIQ [8]	53.4	56.6	57.9	58.0	59.2	58.1	58.2	58.6	64.4	63.3	**65.6**	65.0
	↓ NIQE [10]	4.93	5.08	5.17	5.17	5.25	5.25	5.23	5.27	2.89	3.36	**2.73**	3.10
	↓ PI [2]	4.96	5.04	5.08	5.08	5.11	5.13	5.10	5.14	3.21	3.62	**3.09**	3.40
	↑ PSNR (dB)	28.3	28.7	28.8	28.9	**29.1**	28.9	29.0	29.0	26.4	27.3	27.0	28.0
	↑ TOPIQ [3]	.532	.539	.542	.543	.558	.542	.547	.551	.652	.655	**.673**	.672
	↑ AHIQ [9]	.295	.287	.288	.292	.302	.292	.298	.299	.305	.338	.332	**.360**
	↑ CLIP. [12]	.295	.340	.367	.373	.443	.400	.418	.409	.616	.621	.632	**.636**
	↓ DISTS [4]	.223	.229	.234	.234	.234	.238	.236	.236	.127	.144	**.119**	.133
	↓ FID [7]	43.3	46.5	47.8	48.6	51.2	48.5	51.4	49.2	35.0	43.1	**31.6**	38.1
	↑ Hyper. [11]	.305	.372	.406	.410	.444	.418	.424	.427	.543	.539	**.568**	.564
47	↓ LPIPS [19]	.432	.410	.404	.402	.394	.405	.399	.396	.294	.266	.276	**.255**
	↑ MUSIQ [8]	42.9	48.4	49.9	50.2	51.9	50.4	50.8	51.4	62.7	61.5	**64.3**	63.6
	↓ NIQE [10]	6.08	5.84	5.86	5.89	6.03	6.01	6.01	6.05	2.80	3.50	**2.62**	3.25
	↓ PI [2]	5.91	5.78	5.77	5.79	5.85	5.85	5.85	5.88	3.16	3.82	**3.02**	3.54
	↑ PSNR (dB)	25.9	26.2	26.3	26.4	**26.5**	26.4	26.5	26.5	23.6	25.0	24.1	25.5
	↑ TOPIQ [3]	.389	.411	.418	.421	.434	.419	.426	.428	.478	.503	.492	**.516**

Table 3. Objective quality of enhanced BPG-compressed images with QP set to 42 and 47. All results are to three significant figures.

QF	Metric	Comp.	[5]	[13]	[18]	[6]	[20]	[16]	[17]	[14]	[15]	Ours w/ [14]	Ours w/ [15]
	↑ AHIQ [9]	.388	.406	.419	.421	.436	.427	.432	.431	.432	.438	.451	**.464**
	↑ CLIP. [12]	.463	.470	.489	.503	.537	.509	.516	.502	.654	.640	**.666**	.653
	↓ DISTS [4]	.225	.164	.168	.167	.159	.171	.166	.163	.075	.081	**.072**	.078
	↓ FID [7]	30.7	24.1	21.8	20.8	17.8	20.5	17.1	17.4	15.3	18.1	**14.7**	15.4
	↑ Hyper. [11]	.352	.405	.441	.451	.499	.463	.476	.474	.549	.560	.570	**.579**
10	↓ LPIPS [19]	.323	.272	.269	.266	.251	.266	.257	.254	.155	.147	.146	**.140**
	↑ MUSIQ [8]	47.5	56.5	59.1	59.4	61.3	59.8	60.1	60.5	64.8	64.5	65.7	**65.9**
	↓ NIQE [10]	6.49	4.76	4.70	4.71	4.83	4.78	4.84	4.81	2.86	3.18	**2.72**	2.94
	↓ PI [2]	5.39	4.69	4.68	4.67	4.74	4.72	4.73	4.73	3.15	3.49	**3.07**	3.26
	↑ PSNR (dB)	27.1	28.6	28.8	28.9	**29.3**	29.0	29.2	29.2	26.8	27.8	27.3	28.2
	↑ TOPIQ [3]	.481	.627	.644	.649	.673	.647	.657	.663	.751	.746	.766	**.768**
	↑ AHIQ [9]	.450	.468	.486	.483	.495	.485	.486	.486	.483	.478	.499	**.500**
	↑ CLIP. [12]	.604	.563	.576	.585	.599	.582	.585	.583	.663	.647	**.675**	.661
	↓ DISTS [4]	.146	.122	.126	.124	.117	.127	.123	.120	.048	.051	**.046**	.048
	↓ FID [7]	10.7	8.27	7.24	6.90	6.02	7.05	6.05	6.56	6.13	6.95	**5.40**	5.50
	↑ Hyper. [11]	.396	.465	.506	.514	.541	.516	.520	.523	.564	.569	.582	**.591**
20	↓ LPIPS [19]	.207	.193	.188	.186	.176	.187	.182	.178	.090	.088	.085	**.083**
	↑ MUSIQ [8]	57.4	62.5	64.0	64.3	65.0	64.3	64.5	64.6	65.4	65.3	65.9	**66.5**
	↓ NIQE [10]	4.90	4.32	4.30	4.29	4.36	4.35	4.34	4.34	2.94	3.11	**2.82**	2.88
	↓ PI [2]	4.48	4.30	4.29	4.27	4.33	4.32	4.31	4.32	3.17	3.39	**3.11**	3.19
	↑ PSNR (dB)	29.6	31.0	31.3	31.5	**31.8**	31.4	31.6	31.6	29.3	30.1	29.8	30.6
	↑ TOPIQ [3]	.714	.798	.809	.813	.829	.810	.818	.823	.870	.865	**.880**	.878

Table 4. Objective quality of enhanced JPEG-compressed images with QF set to 10 and 20. All results are to three significant figures.

QF	Metric	Comp.	[5]	[13]	[18]	[6]	[20]	[16]	[17]	[14]	[15]	Ours w/ [14]	Ours w/ [15]
	$\uparrow$ AHIQ [9]	.479	.497	.509	.510	.517	.512	.508	.510	.498	.498	.511	**.518**
	$\uparrow$ CLIP. [12]	.637	.601	.610	.617	.623	.614	.616	.615	.663	.649	**.672**	.662
	$\downarrow$ DISTS [4]	.112	.100	.103	.102	.095	.103	.101	.099	.037	.038	**.035**	.035
	$\downarrow$ FID [7]	5.38	4.24	3.65	3.41	3.16	3.53	3.23	3.60	3.25	3.89	**2.85**	3.17
	$\uparrow$ Hyper. [11]	.433	.493	.531	.538	.554	.539	.541	.542	.564	.568	.580	**.589**
30	$\downarrow$ LPIPS [19]	.154	.155	.150	.149	.141	.149	.145	.145	.084	.081	.059	**.057**
	$\uparrow$ MUSIQ [8]	60.9	64.6	65.7	65.9	**66.3**	65.8	65.9	65.9	65.1	65.3	65.5	66.1
	$\downarrow$ NIQE [10]	4.22	4.12	4.08	4.08	4.11	4.11	4.11	4.10	3.02	3.10	2.91	**2.90**
	$\downarrow$ PI [2]	4.07	4.10	4.09	4.09	4.10	4.11	4.09	4.11	3.21	3.35	**3.16**	3.18
	$\uparrow$ PSNR (dB)	30.9	32.3	32.7	32.8	**33.1**	32.8	33.0	33.0	30.6	31.3	31.1	31.8
	$\uparrow$ TOPIQ [3]	.820	.862	.870	.872	.882	.870	.876	.878	.906	.901	**.911**	.910
	$\uparrow$ AHIQ [9]	.493	.512	.523	.524	.528	.524	.523	.523	.507	.508	.520	**.529**
	$\uparrow$ CLIP. [12]	.645	.620	.627	.629	.634	.630	.631	.629	.664	.653	**.673**	.663
	$\downarrow$ DISTS [4]	.094	.086	.089	.089	.082	.089	.087	.085	.029	.030	**.027**	.028
	$\downarrow$ FID [7]	3.16	2.52	2.16	2.10	1.94	2.21	2.05	2.19	2.15	2.58	**1.92**	2.10
	$\uparrow$ Hyper. [11]	.451	.508	.545	.550	.563	.548	.548	.546	.565	.572	.583	**.591**
40	$\downarrow$ LPIPS [19]	.125	.131	.127	.126	.118	.126	.123	.124	.049	.048	.046	**.045**
	$\uparrow$ MUSIQ [8]	62.5	65.4	66.3	66.4	**66.7**	66.5	66.5	66.3	65.3	65.4	65.6	66.1
	$\downarrow$ NIQE [10]	3.82	3.93	3.88	3.89	3.92	3.91	3.88	3.93	3.07	3.13	2.96	**2.92**
	$\downarrow$ PI [2]	3.81	3.95	3.94	3.93	3.95	3.95	3.94	4.04	3.25	3.35	**3.19**	3.19
	$\uparrow$ PSNR (dB)	31.8	33.2	33.6	33.7	**34.0**	33.7	33.8	33.8	31.5	32.2	31.9	32.7
	$\uparrow$ TOPIQ [3]	.869	.891	.896	.897	.905	.897	.901	.901	.920	.917	**.923**	.923
	$\uparrow$ AHIQ [9]	.503	.523	.532	.535	.537	.531	.533	.533	.514	.514	.525	**.538**
	$\uparrow$ CLIP. [12]	.644	.631	.638	.641	.642	.639	.640	.638	.664	.653	**.673**	.664
	$\downarrow$ DISTS [4]	.082	.076	.078	.076	.071	.077	.076	.074	.024	.025	**.023**	.023
	$\downarrow$ FID [7]	2.13	1.78	1.56	1.57	1.44	1.54	1.64	1.67	1.55	1.96	**1.32**	1.56
	$\uparrow$ Hyper. [11]	.472	.521	.554	.555	.566	.558	.560	.550	.567	.574	.584	**.591**
50	$\downarrow$ LPIPS [19]	.103	.114	.109	.107	.101	.108	.105	.107	.042	.040	.038	**.037**
	$\uparrow$ MUSIQ [8]	63.4	65.9	66.7	66.8	**66.9**	66.7	66.8	66.5	65.2	65.4	65.6	66.1
	$\downarrow$ NIQE [10]	3.48	3.79	3.75	3.75	3.77	3.76	3.78	3.94	3.09	3.12	2.99	**2.96**
	$\downarrow$ PI [2]	3.62	3.84	3.81	3.81	3.82	3.82	3.82	3.84	3.25	3.33	**3.20**	3.21
	$\uparrow$ PSNR (dB)	32.5	33.9	34.3	34.4	**34.7**	34.4	34.5	34.5	32.2	32.8	32.6	33.4
	$\uparrow$ TOPIQ [3]	.894	.907	.911	.912	.917	.912	.914	.914	.928	.925	**.930**	.929

Table 5. Objective quality of enhanced JPEG-compressed images with QF set to 30, 40, and 50. All results are to three significant figures.

Metric	[5]	[13]	[18]	[6]	[20]	[16]	[17]	[14]	[15]	Ours w/ [14]	Ours w/ [15]
AHIQ [9]	-4.79	-8.98	-8.58	-11.8	-9.18	-9.92	-9.76	-9.47	-8.28	-14.7	**-14.8**
CLIP. [12]	+5.58	+3.74	+2.22	-.292	+2.62	+2.09	+2.52	-99.8	-22.2	N/A	-98.9
DISTS [4]	-5.80	-4.95	-5.39	-7.23	-4.81	-5.63	-6.26	-29.5	-27.5	**-31.0**	-28.8
FID [7]	-3.59	-5.18	-5.76	-7.49	-5.63	-7.53	-6.75	-7.57	-6.09	**-8.81**	-8.66
Hyper. [11]	-14.6	-22.5	-24.1	-30.1	-25.8	-28.1	-27.7	N/A	N/A	N/A	N/A
LPIPS [19]	-2.31	-2.92	-3.23	-4.63	-3.09	-3.82	-4.19	-21.5	**-22.1**	-20.2	-20.8
MUSIQ [8]	-12.2	-16.7	-17.4	-21.3	-17.9	-18.5	-19.5	-74.1	-80.6	N/A	N/A
PSNR (dB)	-8.02	-9.65	-10.3	**-12.0**	-10.2	-11.3	-11.3	+1.68	-2.99	-1.05	-5.92
TOPIQ [3]	-6.65	-7.65	-7.94	-9.45	-7.72	-8.45	-8.88	-13.8	-13.3	**-15.1**	-14.9

Table 6. BD-BR (%) performance applied to JPEG-compressed images. Negative values indicate a reduction in bit rate for the same quality. The notation "N/A" is used where the output result is excessively large for presentation. All results are to three significant figures.

tographs. In *2019 IEEE/CVF conference on computer vision and pattern recognition (CVPR)*. IEEE, 2019. 2, 3, 4

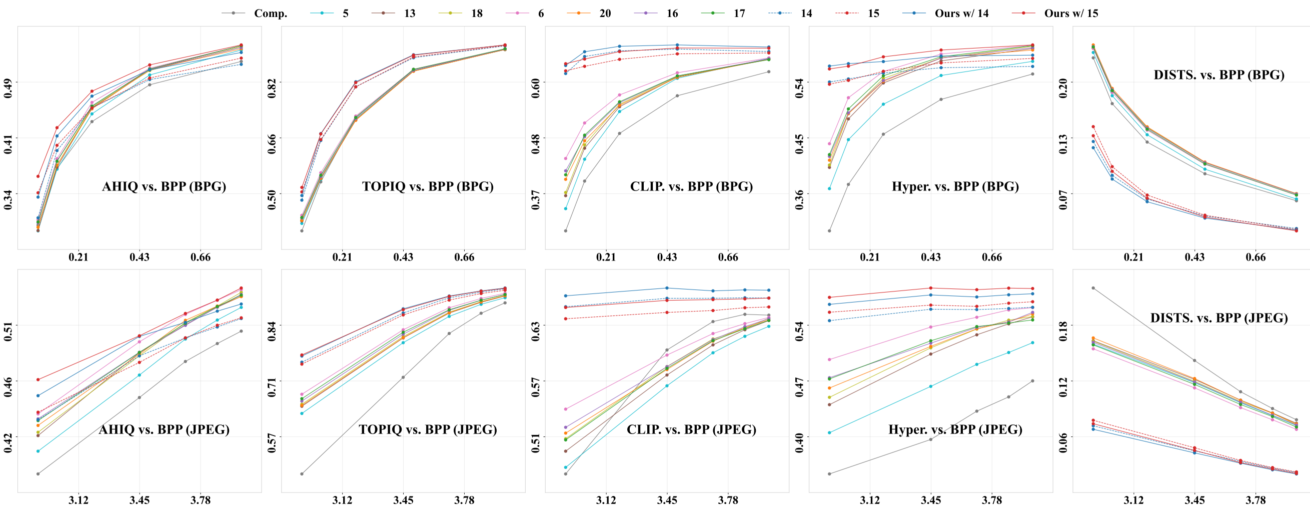

Figure 2. Rate-distortion curves comparing bits per pixel (BPP) against distortion measured by various metrics.

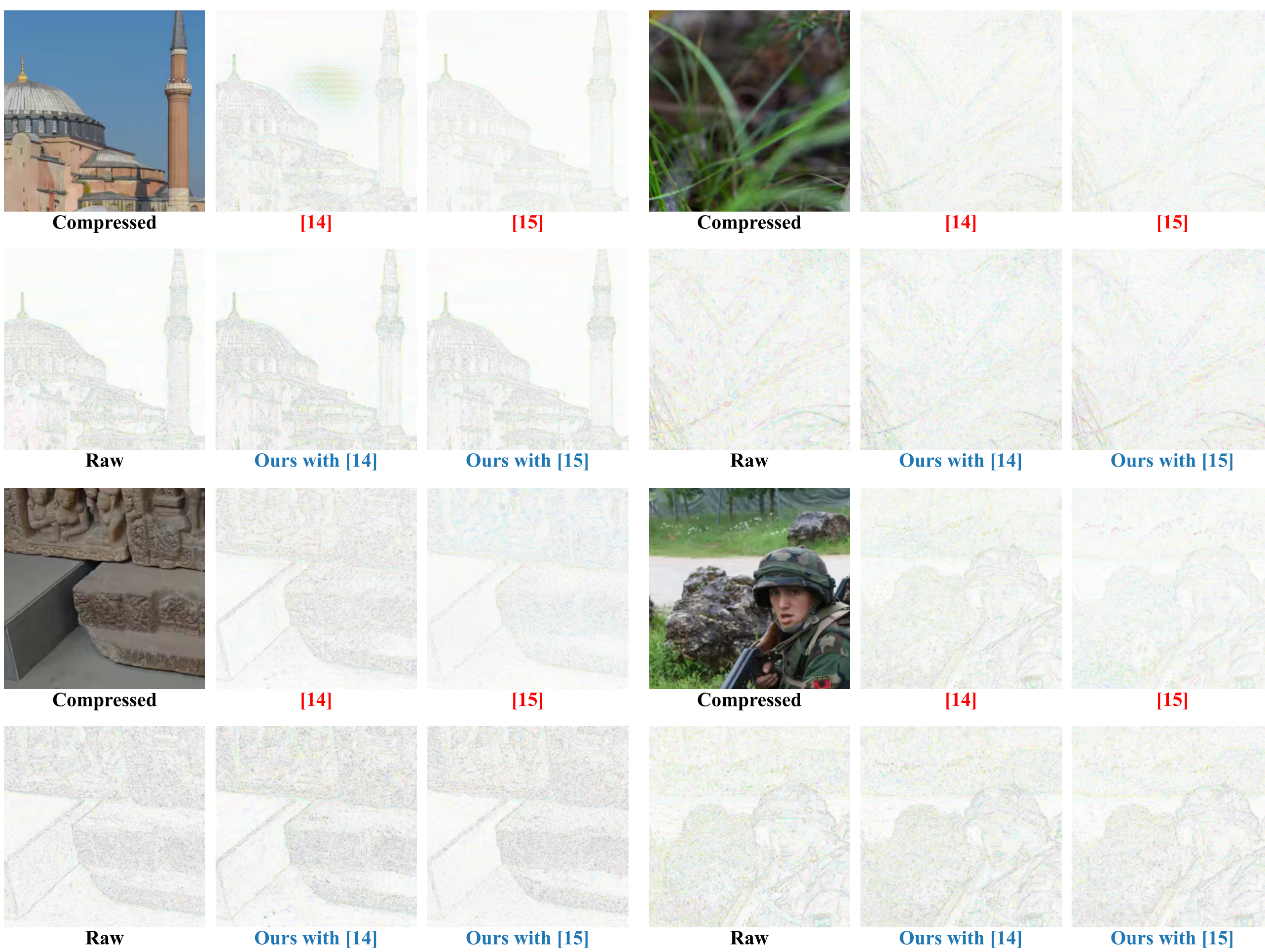

Figure 3. Visualization of residual to the compressed image.

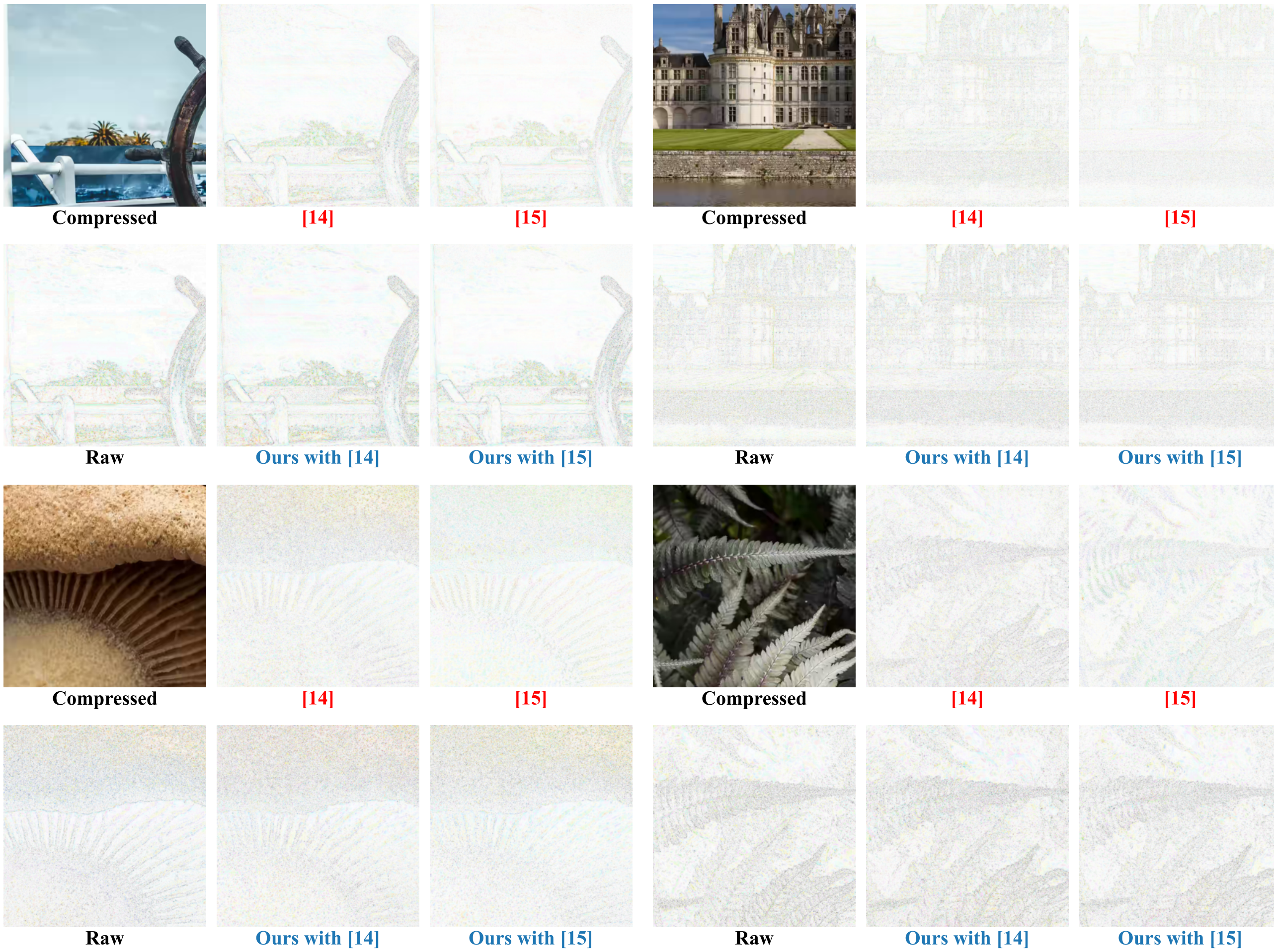

Figure 4. Visualization of residual to the compressed image.

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