Supplementary Material of MoE-DiffIR: Task-customized Diffusion Priors for Universal Compressed Image Restoration

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In this document, we first illustrate more details of MoE-Prompts in Sec. 1. Then, we provide more quantitative results in Sec. 2. Finally, we show more visual comparisons in Sec. 3.

1 More Details of MoE-Prompt

In this section, we provide additional details of MoE-Prompt Module.

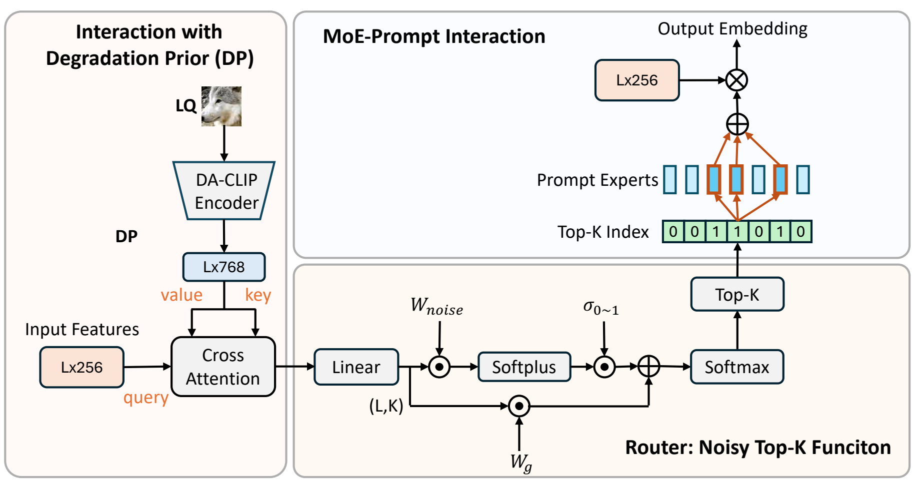

Fig. 1: More details about working pipeline in MoE-Prompt Module. Input features interact with degradation prior through Cross Attention [26]. Then router uses Noisy Top-K function to choose a combination of K prompts, which are first aggregated through summation and then multiplied to input features.

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As depicted in Fig. 1, we use pre-trained image controller offered by DA-CLIP [18] to extract distortion information from low quality image. It is worth noting that DACLIP, having been trained on various tasks, possesses robustness across multiple tasks, including the ability to extract features specific to individuals. Consequently, we did not fine-tune this model on our CIR dataset. This degradation prior (DP) interacts with input features through Cross Attention [26]. Subsequently, we select a combination of K prompts using the Noisy Top-K function [22] mentioned in the main text. Here W_{noise} and W_g are learnable parameters. These K prompts are first aggregated through summation, then followed by a matrix multiplication with the input features, ultimately yielding the output embedding.

In this section, we further demonstrate the effectiveness of our proposed Mixture of Experts (MoE) Prompts. In particular, compared to the Single Prompt [19] or Multiple Weighted Prompts approaches [3,16,18,21], our MoE-based scheduling mechanism enables prompts to independently learn more informative and distinct features of different compression distortions. Accordingly, we measure the cosine similarity between different prompts as a means to represent whether the prompts have learned independent features [1,9,24]. In this context, a higher cosine similarity indicates that the prompts have learned more uniform knowledge, while a lower cosine similarity suggests that each prompt has acquired more independent information, corresponding to different types of distortion. The comparison results with multiple weighted prompts are illustrated in Fig. 2. It can be observed that 7 prompts in the multiple weighted prompts approach are quite similar, indicating that they have learned more homogenized distortion information, leading to low utilization among the prompts. In contrast, the feature similarity among our proposed MoE-Prompt is significantly lower, suggesting that each prompt is more independent and better equipped to handle various distortions, thereby maximizing the utilization of the prompts.

2 More Quantitative Results

2.1 The effect of VAE fine-tuning

Here, we present the PSNR values in Table 1 of the reconstructed images in three designated settings: using only pre-trained VAE, training a VAE from scratch, and employing the Decoder Compensator (our method). From Table 1, it is evident that our method significantly enhances fidelity in terms of objective metrics. Training the VAE from scratch yields inferior results, primarily due to the substantial data requirement for achieving a well-performing VAE.

2.2 More detailed comparison with other methods

In this section, we provided the detailed experimental results for each compression configuration. Here, considering the fast development of image restoration [8,12–15], we compare our methods with several typical IR methods, including one GAN-based methods RealESRGAN [30], one transformer-based method

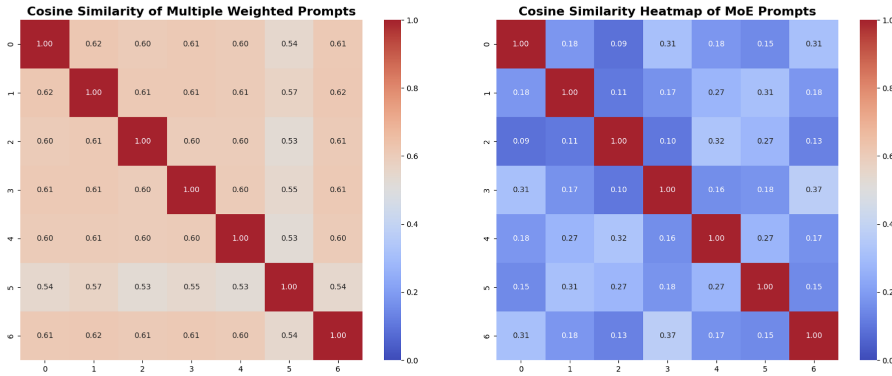

Fig. 2: A comparison of cosine similarity heatmaps for two different designs of prompts: Multiple Weighted Prompts and MoE (Mixture of Experts) prompts. Each heatmap visualizes the pairwise cosine similarities among seven prompts, with color intensity reflecting the degree of similarity.

Table 1: Different VAE training settings (The rightmost is our method). Results are tested on LIVE1 [23].

VAE Settings	Not fine-tune or train VAE	Train VAE from scrarch	Fine-tune VAE decoder (Ours)
PSNR/SSIM (Average on 21 tasks)	22.70/0.646	25.12/0.705	29.03/0.812

PromptIR [21], four Diffusion-based methods StableSR [29], DiffBIR [17], PASD [32] and SUPIR [33]. All methods are reproduced on our proposed CIR dataset. However, it is worth noting that, as SUPIR does not provide the official training code, we directly utilize the pre-trained model offered by the code repositories of SUPIR for sampling purposes. To further assess the subjective quality of the generated images, we also expand our perceptual metrics to include two no-reference (NR) metrics: ClipIQA [28] and ManIQA [31]. Here, we use IQA-PyTorch [6] to implement these metrics with model card 'clipiqa+' and 'maniqa-pipal' respectively. We conduct comprehensive tests for each codec across three different levels of distortion. Results are presented from Table 2 to Table 8. It is observed that our proposed MoE-DiffIR not only significantly outperforms other diffusion-based models in metrics with Ground Truth, such as PSNR, SSIM, LPIPS, and FID, but also demonstrates competitive strength in the no-reference (NR) metrics: ClipIQA and ManIQA.

3 More Visual Results

We provide additional visual comparisons for MoE-DiffIR on Compressed Image Restoration(CIR) tasks. The results are shown in Fig. 3, Fig. 4 and Fig. 5. We conducted tests from low bitrates (HM, QP=37) to high bitrates (VTM, QP=47). From the visual results, we can observe that at higher bitrates, our

Table 2: Quantitative comparison for compressed image restoration on JPEG [27] Codec with three distortion levels. Results are tested on with different metrics in terms of PSNR↑, SSIM↑, LPIPS↓, FID↓, ClipIQA↑ and ManIQA↑. Red and blue colors represent the best and second best performance, respectively.(Suggested to zoom in for better visualization.) *All comparison methods are reproduced on our constructed CIR datasets except for SUPIR [33].*

Dataset	Methods	JPEG																	
		Q=10						Q=15						Q=20					
		PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA	PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA	PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA
LIVE1 [23]	PromptIR [21]	30.11	0.856	0.2557	138.59	0.4987	0.5134	31.59	0.89	0.2064	108.65	0.5271	0.5189	32.56	0.91	0.1773	86.2	0.5263	0.4925
	PASD [32]	28.27	0.808	0.1648	94.56	0.6104	0.6211	28.33	0.795	0.0839	68.29	0.6409	0.6595	28.56	0.815	0.0678	48.54	0.6623	0.6821
	SUPIR [33]	27.11	0.696	0.1590	95.37	0.6354	0.6031	27.35	0.746	0.1237	67.85	0.6890	0.6128	27.77	0.799	0.0934	49.90	0.6838	0.6619
	RealESRGAN [30]	28.88	0.826	0.1750	96.22	0.5561	0.5784	30.48	0.866	0.1382	72.98	0.5851	0.6345	31.41	0.889	0.1138	59.64	0.6013	0.6615
	DiffBIR [17]	28.32	0.810	0.1489	90.92	0.6217	0.6331	28.38	0.800	0.0802	63.97	0.6873	0.6418	28.56	0.827	0.0695	46.81	0.6720	0.6778
	StableSR [29]	29.18	0.824	0.1356	88.00	0.6146	0.5699	30.33	0.861	0.1032	65.45	0.6359	0.5962	31.07	0.881	0.0818	51.12	0.6425	0.5987
	Ours	29.36	0.824	0.1230	82.16	0.6338	0.6475	30.64	0.863	0.0917	60.92	0.6677	0.6791	31.49	0.885	0.0746	45.07	0.6822	0.6993
Classic5 [34]	PromptIR [21]	34.75	0.938	0.1204	68.32	0.4873	0.5283	35.81	0.951	0.1107	53.08	0.4987	0.5154	36.41	0.957	0.1062	48.12	0.5384	0.5237
	PASD [32]	26.87	0.821	0.1071	65.26	0.5986	0.6653	27.12	0.832	0.0981	49.31	0.6943	0.6801	28.91	0.863	0.0824	40.38	0.7182	0.6719
	SUPIR [33]	27.05	0.817	0.1205	69.23	0.6064	0.6832	28.00	0.826	0.1096	50.62	0.6213	0.6917	29.10	0.858	0.1029	41.94	0.7289	0.6953
	RealESRGAN [30]	32.38	0.896	0.1186	73.16	0.6139	0.6284	33.34	0.919	0.1098	48.24	0.6434	0.6394	33.91	0.929	0.1035	48.06	0.6447	0.6560
	DiffBIR [17]	29.68	0.835	0.1121	66.23	0.6587	0.6401	30.56	0.865	0.1010	52.55	0.6416	0.661	30.91	0.879	0.0947	48.06	0.6600	0.6474
	StableSR [29]	30.58	0.858	0.1299	52.24	0.5708	0.6309	31.23	0.875	0.1200	47.30	0.6121	0.6580	31.42	0.891	0.1181	41.36	0.6374	0.6692
	Ours	31.67	0.870	0.1008	49.01	0.6713	0.6840	32.43	0.894	0.0917	41.55	0.6789	0.6964	32.80	0.905	0.0781	31.93	0.6805	0.7131
BSDS500 [4]	PromptIR [21]	31.53	0.868	0.1795	94.34	0.4398	0.5192	31.71	0.879	0.1868	98.49	0.4786	0.4893	32.6	0.895	0.1709	69.66	0.5027	0.5384
	PASD [32]	26.92	0.703	0.1226	86.97	0.5924	0.592	27.89	0.747	0.078	70.45	0.6178	0.5946	28.34	0.825	0.0795	55.36	0.6041	0.6022
	SUPIR [33]	27.31	0.666	0.1487	81.08	0.6631	0.6279	27.81	0.718	0.0787	74.37	0.6671	0.6410	28.55	0.754	0.0954	53.43	0.7017	0.6652
	RealESRGAN [30]	29.96	0.844	0.1596	84.27	0.4985	0.5774	29.90	0.834	0.1588	86.70	0.5675	0.5902	30.86	0.866	0.1270	73.33	0.5833	0.6184
	DiffBIR [17]	28.46	0.805	0.1336	90.83	0.6251	0.6122	28.62	0.790	0.0847	72.18	0.6486	0.6274	28.92	0.834	0.0855	57.29	0.6574	0.6344
	StableSR [29]	30.22	0.839	0.1186	73.33	0.6111	0.6180	30.46	0.839	0.1239	73.43	0.5901	0.6302	31.12	0.862	0.0957	57.06	0.6405	0.6537
	Ours	30.66	0.848	0.1215	78.95	0.6339	0.6429	30.86	0.859	0.0974	70.16	0.6414	0.6568	31.53	0.868	0.0829	54.90	0.6607	0.6723
DIV2K [2]	PromptIR [21]	29.84	0.868	0.2223	125.47	0.4893	0.5102	31.34	0.902	0.1836	92.66	0.5075	0.5123	32.25	0.919	0.1577	78.36	0.5492	0.5239
	PASD [32]	27.52	0.652	0.1161	86.03	0.6162	0.6135	27.85	0.692	0.0859	59.39	0.6429	0.6488	28.77	0.708	0.0697	47.42	0.6659	0.6654
	SUPIR [33]	26.77	0.644	0.1940	89.95	0.6476	0.6264	27.26	0.686	0.1223	60.34	0.6637	0.6825	28.65	0.710	0.0922	60.40	0.7043	0.7034
	RealESRGAN [30]	28.06	0.832	0.1675	93.36	0.5889	0.5739	29.64	0.872	0.1294	70.01	0.6120	0.6213	30.46	0.893	0.1103	60.02	0.6250	0.6421
	DiffBIR [17]	27.66	0.787	0.1198	87.57	0.5753	0.6245	27.97	0.797	0.0840	56.50	0.6211	0.6347	28.34	0.832	0.0657	53.45	0.6357	0.6892
	StableSR [29]	28.44	0.833	0.1373	79.83	0.6211	0.5749	29.60	0.869	0.1008	58.64	0.6402	0.5904	30.29	0.887	0.0819	49.18	0.6429	0.5968
	Ours	28.69	0.836	0.1158	69.98	0.6453	0.6394	30.02	0.874	0.0858	52.66	0.6757	0.6689	30.86	0.895	0.0702	44.62	0.6868	0.6826
ICB [10]	PromptIR [21]	30.24	0.877	0.2559	211.04	0.3778	0.4928	32.11	0.9	0.1944	177.48	0.4354	0.5342	32.65	0.911	0.1836	114.52	0.4987	0.5439
	PASD [32]	27.01	0.627	0.2096	144.45	0.5461	0.5893	27.86	0.676	0.1765	107.91	0.5712	0.6083	28.39	0.701	0.1347	94.66	0.5629	0.6099
	SUPIR [33]	27.03	0.635	0.1662	146.78	0.5647	0.6115	27.89	0.677	0.1292	115.64	0.6195	0.6680	28.42	0.706	0.1003	102.37	0.6232	0.6894
	RealESRGAN [30]	29.19	0.847	0.1788	152.61	0.4805	0.5679	30.41	0.882	0.1363	131.82	0.5165	0.6052	31.07	0.899	0.1179	107.56	0.5436	0.6325
	DiffBIR [17]	29.26	0.819	0.1477	141.85	0.4204	0.5639	29.67	0.839	0.0994	109.20	0.5105	0.6209	30.24	0.852	0.0786	88.11	0.5773	0.6428
	StableSR [29]	29.98	0.849	0.1578	151.07	0.4817	0.5955	31.11	0.879	0.1111	124.86	0.5490	0.6310	31.90	0.898	0.0951	100.75	0.5616	0.6537
	Ours	30.27	0.851	0.1365	123.71	0.5237	0.6188	31.64	0.887	0.1016	102.49	0.5530	0.6449	32.53	0.906	0.0795	76.59	0.5837	0.6688

model excels in text generation compared to other diffusion-model-based restoration methods. Models like SUPIR [33], DiffBIR [17], and PASD [32] may generate incorrect texture information. However, our MoE-DiffIR, benefiting from further fine-tuning of the decoder using MoE-Prompts, produces details that are more faithful to the original image. Additionally, at lower bitrates, as shown in Fig. 3, models such as DiffBIR [17] and SUPIR [33] fail to eliminate background noise interference within the red boxes, whereas our model achieves noticeable restoration effects. This demonstrates the robustness of our MoE-Prompts for universal tasks.

Table 3: Quantitative comparison for compressed image restoration on VVC [5] Codec with three distortion levels. Red and blue colors represent the best and second best performance, respectively.(Suggested to zoom in for better visualization.) *All comparison methods are reproduced on our constructed CIR datasets except for SUPIR [33].*

Dataset	Methods	VVC																	
		Q=47						Q=42						Q=37					
		PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA	PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA	PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA
	PromptIR [21]	27.32	0.744	0.4180	244.70	0.4034	0.4345	29.88	0.831	0.2980	156.55	0.4945	0.5193	32.81	0.899	0.1998	103.84	0.5832	0.5643
	PASD [32]	26.10	0.705	0.2897	137.28	0.5914	0.5198	27.68	0.781	0.1570	108.95	0.6498	0.6218	28.66	0.813	0.0771	58.78	0.6865	0.6884
	SUPIR [33]	27.02	0.677	0.2553	135.35	0.5504	0.5058	27.56	0.709	0.1496	104.99	0.5668	0.6342	27.80	0.755	0.0954	58.86	0.6797	0.6719
LIVE1 [23]	RealESRGAN [30]	26.59	0.708	0.3168	204.32	0.4449	0.4644	28.64	0.792	0.1900	117.27	0.5444	0.5985	30.68	0.859	0.1178	73.89	0.6105	0.6644
	DiffBIR [17]	26.20	0.704	0.2733	131.27	0.4826	0.5259	27.77	0.789	0.1539	101.67	0.5338	0.5825	28.66	0.820	0.0790	53.53	0.7053	0.6750
	StableSR [29]	26.14	0.678	0.2661	152.15	0.5355	0.5250	28.44	0.775	0.1463	87.48	0.6062	0.5767	30.88	0.859	0.0912	55.72	0.6432	0.6084
	Ours	26.20	0.679	0.2317	128.55	0.6110	0.5469	28.73	0.785	0.1296	85.44	0.6682	0.6387	31.34	0.866	0.0720	52.50	0.6963	0.6906
	PromptIR [21]	31.80	0.871	0.2217	211.85	0.4693	0.4356	34.36	0.926	0.1543	145.53	0.4838	0.5024	36.02	0.951	0.1225	88.32	0.5395	0.5398
	PASD [32]	26.56	0.749	0.1594	130.36	0.5492	0.5966	27.94	0.770	0.1370	78.03	0.5864	0.6539	28.85	0.819	0.1178	50.91	0.6239	0.6572
	SUPIR [33]	26.64	0.745	0.1686	133.05	0.5715	0.6503	28.05	0.764	0.1402	79.93	0.6245	0.6806	28.65	0.813	0.1156	49.87	0.6540	0.6907
Classic5 [34]	RealESRGAN [30]	30.81	0.837	0.1654	133.28	0.5437	0.6428	32.78	0.893	0.0918	75.88	0.6046	0.6792	34.10	0.922	0.1017	54.21	0.6191	0.6923
	DiffBIR [17]	28.68	0.772	0.1632	129.46	0.6018	0.612	29.54	0.806	0.1389	77.86	0.6284	0.6633	30.70	0.854	0.1201	49.33	0.7345	0.6724
	StableSR [29]	29.08	0.782	0.1542	128.61	0.5101	0.5126	30.50	0.825	0.1232	69.58	0.5381	0.5548	31.12	0.860	0.1179	55.59	0.5735	0.5905
	Ours	29.67	0.794	0.1344	109.01	0.5887	0.6366	31.33	0.857	0.1004	74.96	0.6535	0.6786	32.02	0.883	0.0953	50.86	0.6782	0.6911
	PromptIR [21]	28.63	0.756	0.3483	211.32	0.3639	0.4043	29.76	0.797	0.2982	173.82	0.4349	0.4783	32.56	0.880	0.1990	101.61	0.5020	0.5639
	PASD [32]	26.28	0.721	0.2412	142.94	0.5498	0.5649	26.46	0.723	0.1866	114.71	0.5745	0.5816	27.77	0.804	0.0874	69.46	0.6011	0.6044
	SUPIR [33]	25.84	0.684	0.2409	139.06	0.4958	0.4793	27.40	0.748	0.1849	113.43	0.5601	0.5352	28.24	0.820	0.1019	64.65	0.6194	0.6477
BSDS500 [4]	RealESRGAN [30]	27.02	0.713	0.2819	177.97	0.4233	0.4986	27.85	0.749	0.2303	134.54	0.4957	0.5508	29.85	0.832	0.1433	79.33	0.5593	0.6218
	DiffBIR [17]	27.54	0.731	0.2519	145.51	0.5478	0.5814	27.93	0.778	0.1833	118.30	0.6269	0.6269	28.45	0.811	0.0972	70.46	0.6625	0.6824
	StableSR [29]	27.61	0.704	0.2385	135.55	0.5319	0.5528	28.34	0.740	0.1920	102.36	0.5953	0.5954	30.30	0.823	0.1187	63.24	0.6605	0.6618
	Ours	27.46	0.693	0.2141	114.71	0.6136	0.5916	28.35	0.734	0.1718	87.68	0.6481	0.6244	31.00	0.838	0.0871	52.38	0.6723	0.6652
	PromptIR [21]	26.54	0.743	0.3862	210.77	0.3982	0.4023	29.33	0.840	0.2350	138.07	0.4873	0.4987	32.35	0.912	0.1671	89.03	0.5342	0.5645
	PASD [32]	25.39	0.660	0.2234	129.90	0.6030	0.5414	27.16	0.752	0.1187	90.34	0.6510	0.6255	28.18	0.802	0.0643	68.37	0.6819	0.6802
	SUPIR [33]	25.02	0.656	0.2972	132.31	0.5538	0.5986	26.59	0.753	0.1381	96.42	0.6498	0.6750	27.80	0.789	0.1145	70.68	0.7117	0.7067
DIV2K [2]	RealESRGAN [30]	25.65	0.706	0.2953	172.56	0.4691	0.4746	27.80	0.799	0.1820	101.53	0.5677	0.5920	29.86	0.871	0.1161	68.52	0.6226	0.6499
	DiffBIR [17]	25.49	0.692	0.2336	124.98	0.5299	0.4534	27.44	0.773	0.1324	93.19	0.6099	0.6009	28.26	0.823	0.0743	62.87	0.6239	0.6816
	StableSR [29]	25.67	0.700	0.2333	143.66	0.5582	0.5441	25.67	0.700	0.1433	143.66	0.5582	0.5441	29.97	0.869	0.0779	50.85	0.6448	0.6013
	Ours	25.40	0.682	0.2123	124.29	0.6331	0.5714	28.02	0.795	0.1192	75.50	0.6660	0.6369	30.74	0.880	0.0634	43.10	0.6988	0.6805
	PromptIR [21]	27.95	0.776	0.3774	265.15	0.3398	0.4234	29.25	0.819	0.2677	219.37	0.3856	0.5045	30.84	0.853	0.1942	131.38	0.4534	0.5634
	PASD [32]	26.13	0.655	0.2229	215.01	0.4889	0.5601	26.43	0.706	0.1849	143.21	0.5468	0.5884	27.84	0.764	0.1492	104.89	0.5476	0.6040
	SUPIR [33]	26.20	0.664	0.2858	219.91	0.4107	0.5423	26.46	0.711	0.2088	153.14	0.4632	0.6196	27.87	0.769	0.1025	106.89	0.6492	0.7404
ICB [10]	RealESRGAN [30]	27.03	0.750	0.2852	245.32	0.3815	0.4899	27.92	0.795	0.1967	172.54	0.4554	0.5819	28.72	0.824	0.1535	148.61	0.5112	0.6202
	DiffBIR [17]	27.42	0.738	0.2612	218.70	0.4800	0.5424	27.91	0.776	0.1577	147.74	0.4699	0.6100	28.75	0.811	0.1048	98.29	0.5847	0.6353
	StableSR [29]	27.16	0.746	0.2578	235.08	0.4217	0.5100	28.43	0.793	0.1694	156.94	0.5045	0.6013	29.79	0.829	0.1199	105.49	0.5819	0.6488
	Ours	27.04	0.717	0.2237	204.02	0.5143	0.5552	28.51	0.787	0.1422	134.79	0.5473	0.6146	30.62	0.840	0.0960	94.71	0.5968	0.6456

Table 4: Quantitative comparison for compressed image restoration on HEVC [25] Codec with three distortion levels. Red and blue colors represent the best and second best performance, respectively.(Suggested to zoom in for better visualization.) *All comparison methods are reproduced on our constructed CIR datasets except for SUPIR [33].*

Dataset	Methods	HEVC																	
		Q=47						Q=42						Q=37					
		PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA	PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA	PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA
	PromptIR [21]	26.84	0.730	0.4210	256.55	0.3897	0.3763	29.54	0.821	0.3113	158.93	0.4763	0.4873	32.25	0.891	0.2091	102.27	0.5435	0.5763
	PASD [32]	25.95	0.690	0.2690	153.83	0.5729	0.4910	27.79	0.758	0.1755	109.31	0.6347	0.6074	28.76	0.817	0.1009	63.54	0.6654	0.6697
	SUPIR [33]	26.01	0.628	0.2363	153.60	0.4357	0.5204	26.87	0.675	0.1848	108.53	0.6234	0.5947	27.52	0.734	0.1104	63.95	0.6729	0.6869
LIVE1 [23]	RealESRGAN [30]	25.92	0.688	0.3353	219.63	0.4490	0.4429	28.24	0.781	0.2154	126.59	0.5180	0.5673	30.78	0.858	0.1299	72.78	0.6043	0.6459
	DiffBIR [17]	26.03	0.695	0.2679	148.82	0.5291	0.4936	27.75	0.769	0.1667	103.77	0.5764	0.5550	28.80	0.822	0.1024	59.68	0.6855	0.6560
	StableSR [29]	25.71	0.656	0.2925	162.94	0.5308	0.4983	28.18	0.767	0.1704	94.55	0.5755	0.5652	30.69	0.855	0.0905	60.51	0.6345	0.6021
	Ours	25.86	0.665	0.2491	148.11	0.5879	0.5253	28.49	0.777	0.1456	90.56	0.6436	0.6249	31.14	0.862	0.0818	57.31	0.6815	0.6788
	PromptIR [21]	31.41	0.856	0.2360	240.86	0.4564	0.5636	34.10	0.920	0.1606	153.37	0.4983	0.4983	36.11	0.950	0.1198	78.91	0.5593	0.5638
	PASD [32]	24.65	0.701	0.1616	133.25	0.5833	0.6046	25.99	0.802	0.1299	82.91	0.6243	0.6474	27.42	0.846	0.1025	59.57	0.6989	0.6463
	SUPIR [33]	27.05	0.695	0.1610	139.55	0.6036	0.6269	25.20	0.796	0.1362	88.90	0.6704	0.6713	26.93	0.840	0.1044	62.91	0.7099	0.6894
Classic5 [34]	RealESRGAN [30]	30.32	0.812	0.1936	155.51	0.4966	0.6011	32.70	0.884	0.0968	95.23	0.5876	0.6644	34.28	0.922	0.0894	61.77	0.6151	0.6883
	DiffBIR [17]	29.31	0.729	0.1579	137.19	0.5885	0.6230	29.22	0.828	0.1315	87.50	0.6158	0.6323	30.10	0.869	0.1058	59.85	0.6412	0.6705
	StableSR [29]	28.98	0.770	0.1706	124.66	0.5461	0.5775	30.65	0.824	0.1187	77.95	0.5478	0.6047	31.55	0.868	0.1076	55.32	0.6268	0.6751
	Ours	29.22	0.767	0.1521	113.28	0.5735	0.6293	31.40	0.856	0.1005	76.92	0.6380	0.6757	32.62	0.893	0.0844	58.27	0.6671	0.6946
	PromptIR [21]	28.16	0.743	0.3573	209.11	0.3758	0.3984	29.34	0.784	0.3109	162.68	0.4347	0.4859	32.13	0.871	0.2021	96.95	0.5034	0.5464
	PASD [32]	25.14	0.770	0.2455	156.82	0.5425	0.5521	26.29	0.687	0.1867	100.73	0.5599	0.5706	26.79	0.784	0.0938	62.77	0.5858	0.5961
	SUPIR [33]	25.18	0.633	0.2685	148.70	0.4803	0.4526	26.40	0.803	0.1826	99.99	0.5909	0.5109	27.62	0.792	0.1173	72.87	0.6729	0.6270
BSDS500 [4]	RealESRGAN [30]	26.73	0.697	0.2971	176.02	0.4183	0.4575	27.59	0.737	0.2508	145.59	0.4809	0.5167	29.74	0.829	0.1587	90.37	0.5535	0.5991
	DiffBIR [17]	26.70	0.742	0.2468	158.47	0.5287	0.5627	27.98	0.769	0.1861	105.71	0.5604	0.5880	28.69	0.809	0.1023	69.41	0.6451	0.6633
	StableSR [29]	27.27	0.691	0.2494	144.33	0.5037	0.5048	28.25	0.736	0.2027	116.32	0.5407	0.5519	30.39	0.825	0.1184	64.90	0.6393	0.6408
	Ours	27.04	0.672	0.2380	127.24	0.6015	0.5733	28.20	0.729	0.1825	100.56	0.6499	0.6007	30.88	0.834	0.0943	60.88	0.6571	0.6479
	PromptIR [21]	26.17	0.730	0.3952	211.22	0.3895	0.3784	28.96	0.831	0.2539	142.75	0.4987	0.5034	31.99	0.905	0.1540	85.08	0.5874	0.5454
	PASD [32]	25.18	0.624	0.2349	131.79	0.5676	0.5020	26.38	0.719	0.1320	100.22	0.6245	0.5992	26.88	0.770	0.0814	60.48	0.6698	0.6645
	SUPIR [33]	24.38	0.621	0.3081	133.70	0.4277	0.5505	25.77	0.715	0.1289	101.01	0.5924	0.6456	26.26	0.765	0.0923	75.90	0.7022	0.6934
DIV2K [2]	RealESRGAN [30]	25.19	0.684	0.3152	172.24	0.4509	0.4359	27.53	0.789	0.2043	109.22	0.5589	0.5583	29.86	0.869	0.1248	69.58	0.6172	0.6377
	DiffBIR [17]	24.93	0.668	0.2511	135.43	0.5427	0.4131	27.34	0.769	0.1442	93.48	0.5858	0.5754	28.62	0.817	0.0833	59.65	0.7113	0.6711
	StableSR [29]	25.30	0.683	0.2636	144.99	0.5403	0.5233	27.71	0.789	0.1498	88.79	0.5970	0.5696	30.00	0.868	0.0835	52.62	0.6309	0.5960
	Ours	25.10	0.668	0.2356	128.47	0.6057	0.5419	27.78	0.787	0.1345	78.52	0.6495	0.6192	30.60	0.877	0.0710	46.90	0.6855	0.6706
	PromptIR [21]	27.38	0.796	0.3821	285.64	0.3874	0.4345	29.24	0.846	0.2505	225.11	0.4034	0.4985	29.93	0.859	0.2216	159.91	0.4323	0.5248
	PASD [32]	25.74	0.634	0.2381	249.77	0.4666	0.5537	27.34	0.728	0.1696	169.59	0.5305	0.5863	27.98	0.755	0.1327	114.02	0.5351	0.5923
	SUPIR [33]	25.77	0.640	0.2503	254.00	0.3043	0.5097	27.39	0.730	0.2192	171.49	0.4515	0.5414	28.00	0.760	0.1118	121.61	0.5039	0.6089
ICB [10]	RealESRGAN [30]	26.95	0.763	0.2819	269.30	0.3502	0.4900	28.98	0.824	0.2070	176.89	0.4285	0.5597	29.07	0.834	0.1688	156.53	0.4868	0.5963
	DiffBIR [17]	27.29	0.739	0.2313	243.94	0.4186	0.5038	28.19	0.789	0.1631	165.59	0.4616	0.6264	29.38	0.813	0.1055	119.38	0.5420	0.6282
	StableSR [29]	27.24	0.760	0.2576	254.68	0.3884	0.4994	29.15	0.812	0.1695	174.69	0.5080	0.5849	30.13	0.838	0.1415	124.17	0.5098	0.6116
	Ours	26.97	0.764	0.2460	230.42	0.4699	0.5542	29.46	0.825	0.1662	163.61	0.5385	0.6034	30.49	0.835	0.1107	119.01	0.5506	0.6229

Table 5: Quantitative comparison for compressed image restoration on WebP [11] Codec with three distortion levels. Red and blue colors represent the best and second best performance, respectively.(Suggested to zoom in for better visualization.) *All comparison methods are reproduced on our constructed CIR datasets except for SUPIR [33].*

Dataset	Methods	WebP																	
		Q=1						Q=5						Q=10					
		PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA	PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA	PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA
LIVE1 [23]	PromptIR [21]	29.30	0.822	0.3031	189.45	0.4251	0.4232	30.69	0.862	0.2418	140.35	0.4698	0.4345	31.47	0.885	0.2053	118.40	0.4983	0.4874
	PASD [32]	27.48	0.733	0.2061	126.26	0.6146	0.5935	27.91	0.780	0.1306	95.79	0.6591	0.6515	28.26	0.800	0.1200	68.64	0.6688	0.6739
	SUPIR [33]	25.92	0.634	0.1852	125.27	0.6137	0.4783	26.39	0.676	0.1368	93.31	0.6356	0.6526	27.77	0.762	0.1034	68.08	0.6709	0.6593
	RealESRGAN [30]	28.02	0.781	0.2139	123.55	0.5147	0.5515	29.10	0.822	0.1611	92.83	0.5785	0.6172	29.73	0.845	0.1341	85.09	0.5938	0.6446
	DiffBIR [17]	27.55	0.749	0.2001	121.68	0.6272	0.5623	28.00	0.786	0.1341	88.97	0.6354	0.6278	28.32	0.801	0.1074	63.55	0.6596	0.6514
	StableSR [29]	28.02	0.770	0.1498	89.11	0.5897	0.5590	29.00	0.811	0.1124	70.37	0.6069	0.5831	29.63	0.835	0.0996	65.92	0.6248	0.5983
	Ours	28.29	0.778	0.1384	86.48	0.6292	0.6079	29.40	0.821	0.1043	64.76	0.6626	0.6573	30.15	0.846	0.0868	60.67	0.6840	0.6823
Classic5 [34]	PromptIR [21]	34.26	0.920	0.1553	118.17	0.4983	0.5463	35.24	0.940	0.1340	93.45	0.5234	0.5975	35.81	0.949	0.1256	72.35	0.5434	0.5438
	PASD [32]	27.14	0.822	0.0971	79.06	0.5919	0.6561	29.20	0.830	0.0985	61.80	0.6169	0.6458	29.79	0.879	0.0865	48.48	0.6428	0.6687
	SUPIR [33]	27.06	0.816	0.1213	86.72	0.6141	0.6588	28.33	0.825	0.1108	65.28	0.6559	0.6688	29.03	0.871	0.0999	56.51	0.6694	0.6853
	RealESRGAN [30]	32.96	0.896	0.1030	104.04	0.5927	0.6623	33.80	0.917	0.0825	89.01	0.6304	0.6782	34.22	0.927	0.0929	76.50	0.6419	0.6880
	DiffBIR [17]	30.63	0.848	0.1018	82.85	0.6088	0.65	30.06	0.872	0.1057	62.99	0.6444	0.6686	29.34	0.904	0.0985	53.43	0.7600	0.6675
	StableSR [29]	31.92	0.858	0.0904	79.89	0.5560	0.6083	32.02	0.873	0.1211	64.99	0.5788	0.6316	32.39	0.884	0.1108	62.42	0.5974	0.6498
	Ours	32.37	0.879	0.0757	79.94	0.6095	0.6676	32.88	0.898	0.0800	59.07	0.6539	0.6785	33.22	0.908	0.0782	46.09	0.6665	0.6867
BSDS500 [4]	PromptIR [21]	29.19	0.793	0.3032	174.36	0.4353	0.4758	30.47	0.838	0.2502	142.05	0.4869	0.5645	31.38	0.866	0.2065	119.93	0.5433	0.5245
	PASD [32]	26.94	0.720	0.2335	121.92	0.5584	0.5689	27.99	0.773	0.1393	97.36	0.5794	0.5888	28.12	0.808	0.1186	86.70	0.5906	0.5977
	SUPIR [33]	25.64	0.688	0.2483	118.58	0.5836	0.5377	26.21	0.757	0.1602	92.57	0.6488	0.5927	26.66	0.776	0.1289	89.22	0.6833	0.6232
	RealESRGAN [30]	27.66	0.747	0.2354	139.45	0.4904	0.5112	28.50	0.789	0.1802	115.90	0.5410	0.5745	29.00	0.816	0.1513	98.14	0.5616	0.6025
	DiffBIR [17]	27.79	0.733	0.2413	123.78	0.5204	0.5141	28.30	0.783	0.1502	100.34	0.6207	0.6004	28.82	0.816	0.1201	87.27	0.6733	0.6271
	StableSR [29]	28.25	0.744	0.1879	119.85	0.5675	0.5604	29.11	0.785	0.1450	93.08	0.6253	0.6231	29.64	0.811	0.1254	78.76	0.6511	0.6475
	Ours	28.24	0.743	0.1604	93.87	0.6173	0.5848	29.24	0.789	0.1236	80.58	0.6498	0.6304	29.90	0.817	0.1061	66.52	0.6644	0.6535
DIV2K [2]	PromptIR [21]	28.75	0.830	0.2634	159.63	0.4085	0.4873	30.18	0.872	0.2051	130.93	0.4501	0.5324	31.19	0.896	0.1727	115.33	0.4743	0.4632
	PASD [32]	25.34	0.685	0.1283	122.32	0.6374	0.6065	26.12	0.733	0.0969	87.78	0.6688	0.6468	27.21	0.750	0.0852	82.64	0.6764	0.6647
	SUPIR [33]	25.00	0.678	0.1960	127.17	0.6172	0.6080	25.67	0.727	0.1279	89.94	0.6762	0.6727	26.84	0.744	0.1151	85.95	0.7020	0.6903
	RealESRGAN [30]	27.33	0.788	0.1968	113.83	0.5440	0.5578	28.26	0.830	0.1481	91.37	0.5988	0.6151	28.90	0.853	0.1255	78.03	0.6128	0.6372
	DiffBIR [17]	27.27	0.757	0.1638	117.77	0.5811	0.5919	27.83	0.775	0.1256	81.79	0.6525	0.6379	28.08	0.803	0.1061	74.25	0.6979	0.6596
	StableSR [29]	27.46	0.783	0.1559	102.93	0.5945	0.5702	28.45	0.826	0.1169	81.87	0.6192	0.5872	29.10	0.851	0.0978	68.81	0.6338	0.5954
	Ours	27.56	0.787	0.1280	84.33	0.6505	0.6159	28.69	0.831	0.0971	66.30	0.6823	0.6578	29.45	0.857	0.0805	55.99	0.6923	0.6746
ICB [10]	PromptIR [21]	28.69	0.839	0.2850	266.06	0.2873	0.3984	29.70	0.870	0.2186	188.20	0.3142	0.3746	30.44	0.889	0.2021	167.74	0.3288	0.3898
	PASD [32]	26.51	0.666	0.1832	156.06	0.5032	0.5764	26.69	0.715	0.1267	139.46	0.5331	0.5904	27.39	0.741	0.1039	119.87	0.5566	0.5921
	SUPIR [33]	26.52	0.677	0.1930	159.03	0.4685	0.6147	26.70	0.715	0.1143	145.86	0.5498	0.6627	26.95	0.742	0.1094	119.55	0.5311	0.7288
	RealESRGAN [30]	28.70	0.814	0.2060	204.22	0.4436	0.5440	29.22	0.848	0.1704	170.33	0.4942	0.5917	29.76	0.869	0.1441	147.14	0.5271	0.6119
	DiffBIR [17]	28.72	0.783	0.1794	161.68	0.4297	0.5568	28.70	0.810	0.1353	136.90	0.5822	0.5698	29.73	0.827	0.1073	112.10	0.5276	0.5838
	StableSR [29]	28.99	0.806	0.1868	169.88	0.4791	0.5705	29.99	0.845	0.1400	141.01	0.5519	0.6180	30.61	0.865	0.1193	117.43	0.5785	0.6404
	Ours	29.22	0.824	0.1599	167.43	0.5134	0.5845	30.40	0.861	0.1211	127.92	0.5670	0.6252	31.31	0.874	0.0954	113.46	0.5954	0.6428

Table 6: Quantitative comparison for compressed image restoration on C_{PSNR} [7] Codec with three distortion levels. Red and blue colors represent the best and second best performance, respectively.(Suggested to zoom in for better visualization.) *All comparison methods are reproduced on our constructed CIR datasets except for SUPIR [33].*

Dataset	Methods	C_{PSNR}																	
		Q=1						Q=2						Q=3					
		PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA	PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA	PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA
LIVE1 [23]	PromptIR [21]	29.36	0.826	0.2863	177.66	0.3951	0.4249	31.07	0.869	0.2301	137.27	0.4543	0.4384	32.10	0.901	0.1859	109.21	0.4897	0.4756
	PASD [32]	27.69	0.787	0.1515	110.09	0.6194	0.6521	28.46	0.811	0.1063	91.21	0.6591	0.6872	28.87	0.831	0.0787	67.76	0.6753	0.7101
	SUPIR [33]	27.23	0.687	0.1625	110.27	0.6778	0.6812	27.62	0.728	0.0963	91.04	0.6708	0.7114	27.88	0.749	0.0633	68.86	0.6922	0.6905
	RealESRGAN [30]	29.00	0.804	0.2027	116.64	0.5270	0.6248	30.15	0.842	0.1390	77.34	0.5872	0.6674	31.07	0.873	0.0985	62.15	0.6103	0.6906
	DiffBIR [17]	27.77	0.789	0.1374	105.84	0.6884	0.6309	28.52	0.819	0.1042	87.71	0.6637	0.6765	28.96	0.829	0.0777	62.58	0.7294	0.7058
	StableSR [29]	28.78	0.797	0.1444	99.80	0.6236	0.6002	29.93	0.837	0.1011	69.92	0.6437	0.6148	30.85	0.865	0.0792	51.87	0.6531	0.6179
	Ours	28.96	0.799	0.1346	96.22	0.6375	0.6493	30.25	0.841	0.0962	68.10	0.6714	0.6846	31.32	0.871	0.0679	50.36	0.6964	0.7071
Classic5 [34]	PromptIR [21]	34.84	0.930	0.1705	174.29	0.5700	0.5638	35.99	0.948	0.1439	144.73	0.5765	0.5634	36.77	0.958	0.1235	141.36	0.5725	0.5783
	PASD [32]	26.16	0.779	0.1325	70.12	0.6274	0.6358	27.16	0.832	0.1259	67.67	0.7038	0.6483	28.39	0.818	0.1222	62.14	0.7166	0.6507
	SUPIR [33]	29.69	0.772	0.1392	73.24	0.6454	0.6757	27.90	0.825	0.1477	73.07	0.7237	0.6723	28.55	0.812	0.1361	67.29	0.7370	0.6876
	RealESRGAN [30]	33.22	0.903	0.1088	94.65	0.6083	0.6876	33.84	0.919	0.1143	67.41	0.6191	0.6873	34.23	0.929	0.0957	78.87	0.6066	0.6933
	DiffBIR [17]	30.37	0.829	0.1354	71.16	0.6543	0.6497	29.13	0.843	0.1278	69.02	0.6641	0.665	30.90	0.850	0.1288	67.20	0.6871	0.6686
	StableSR [29]	31.06	0.835	0.1246	82.49	0.5287	0.5415	31.39	0.847	0.1145	70.46	0.5962	0.5801	31.43	0.858	0.1207	59.36	0.6077	0.5976
	Ours	31.37	0.852	0.1162	71.12	0.6435	0.6635	31.83	0.868	0.1106	63.33	0.6588	0.6745	32.06	0.878	0.1118	60.09	0.6725	0.6794
BSDS500 [4]	PromptIR [21]	29.49	0.792	0.3171	180.11	0.4385	0.4637	30.94	0.841	0.2451	146.89	0.5142	0.4983	32.31	0.881	0.1811	108.08	0.5704	0.5643
	PASD [32]	26.24	0.731	0.2183	107.01	0.5806	0.5898	26.73	0.790	0.1532	91.28	0.5897	0.6005	27.37	0.725	0.0932	70.04	0.6072	0.6108
	SUPIR [33]	27.15	0.722	0.2378	103.94	0.5718	0.5659	27.79	0.811	0.1572	92.69	0.6791	0.6217	28.90	0.755	0.1207	68.28	0.7401	0.6631
	RealESRGAN [30]	28.47	0.769	0.2878	183.85	0.4795	0.5648	29.76	0.817	0.2188	142.74	0.5372	0.6124	30.63	0.853	0.1638	100.63	0.5716	0.6442
	DiffBIR [17]	27.26	0.774	0.2151	112.73	0.6369	0.6111	28.49	0.822	0.1479	94.78	0.6727	0.6437	28.44	0.789	0.0971	71.75	0.6963	0.6749
	StableSR [29]	28.73	0.768	0.2079	130.59	0.5715	0.6152	29.69	0.809	0.1555	97.21	0.6273	0.6534	30.50	0.842	0.1151	72.57	0.6539	0.6796
	Ours	28.99	0.778	0.2047	120.39	0.5734	0.6212	30.14	0.823	0.1451	93.48	0.6319	0.6590	31.23	0.861	0.0970	66.78	0.6608	0.6864
DIV2K [2]	PromptIR [21]	28.93	0.837	0.2234	168.93	0.4081	0.4934	30.62	0.883	0.1903	124.67	0.4642	0.4873	32.07	0.916	0.1433	95.55	0.4970	0.5034
	PASD [32]	27.17	0.773	0.1185	99.36	0.6187	0.6482	27.23	0.790	0.0827	80.84	0.6519	0.6783	27.88	0.795	0.0788	67.40	0.6725	0.6967
	SUPIR [33]	26.62	0.761	0.1240	100.39	0.5893	0.6950	26.79	0.786	0.1268	83.40	0.6786	0.7099	27.58	0.791	0.0631	70.40	0.7217	0.7164
	RealESRGAN [30]	28.10	0.808	0.1954	103.29	0.5311	0.6151	29.24	0.849	0.1335	76.89	0.5861	0.6536	30.03	0.877	0.1041	64.24	0.6111	0.6677
	DiffBIR [17]	27.55	0.781	0.1316	90.85	0.6052	0.6322	28.05	0.804	0.1004	80.02	0.6692	0.6789	28.57	0.828	0.0769	69.37	0.6721	0.7005
	StableSR [29]	27.78	0.798	0.1283	85.34	0.6156	0.5956	28.79	0.837	0.0965	70.08	0.6393	0.6053	29.72	0.870	0.0762	51.50	0.6505	0.6104
	Ours	28.12	0.805	0.1180	75.11	0.6455	0.6445	29.57	0.853	0.0828	68.61	0.6718	0.6732	30.69	0.886	0.0587	43.19	0.6919	0.6919
ICB [10]	PromptIR [21]	29.55	0.851	0.2577	214.99	0.3818	0.4983	30.68	0.884	0.1874	169.02	0.4116	0.4876	31.23	0.906	0.1750	142.75	0.4321	0.4934
	PASD [32]	28.18	0.769	0.2101	142.52	0.5363	0.5877	28.57	0.783	0.1896	109.35	0.5447	0.6001	28.92	0.804	0.1409	102.10	0.5649	0.6103
	SUPIR [33]	28.18	0.771	0.1669	143.76	0.5524	0.6639	28.60	0.798	0.1215	114.27	0.5412	0.6607	28.96	0.820	0.0872	103.39	0.6160	0.7045
	RealESRGAN [30]	29.26	0.834	0.1962	181.02	0.4347	0.5885	30.03	0.863	0.1448	143.30	0.5079	0.6275	30.08	0.879	0.1331	128.78	0.5303	0.6390
	DiffBIR [17]	29.11	0.810	0.1392	133.20	0.5635	0.6327	30.12	0.839	0.1035	104.21	0.5544	0.6319	30.13	0.855	0.0862	92.18	0.5840	0.5920
	StableSR [29]	29.54	0.824	0.1554	141.05	0.5378	0.6258	30.47	0.855	0.1256	109.24	0.5724	0.6511	31.20	0.881	0.1029	93.35	0.6032	0.6674
	Ours	29.96	0.828	0.1370	139.71	0.5576	0.6217	31.34	0.868	0.1004	99.70	0.5779	0.6450	32.46	0.896	0.0748	87.74	0.6109	0.6616

Table 7: Quantitative comparison for compressed image restoration on C_{SSIM} [7] Codec with three distortion levels. Red and blue colors represent the best and second best performance, respectively.(Suggested to zoom in for better visualization.) *All comparison methods are reproduced on our constructed CIR datasets except for SUPIR [33].*

Dataset	Methods	C_{SSIM}																	
		Q=1						Q=2						Q=3					
		PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA	PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA	PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA
LIVE1 [23]	PromptIR [21]	26.73	0.784	0.3817	202.35	0.3782	0.3927	27.94	0.829	0.3289	156.56	0.4355	0.4937	29.17	0.866	0.2747	121.51	0.4727	0.4841
	PASD [32]	25.75	0.736	0.1638	107.63	0.5679	0.5905	26.37	0.759	0.1398	82.90	0.5913	0.6260	27.23	0.790	0.1094	69.23	0.6233	0.6606
	SUPIR [33]	25.24	0.631	0.2013	109.07	0.6997	0.6227	25.42	0.666	0.1229	82.71	0.6632	0.6931	25.78	0.687	0.0832	69.23	0.6718	0.7029
	RealESRGAN [30]	26.07	0.763	0.2538	144.93	0.4709	0.5654	27.23	0.807	0.1874	98.22	0.5227	0.6182	27.95	0.837	0.1547	81.09	0.5512	0.6433
	DiffBIR [17]	25.82	0.739	0.1695	104.11	0.5118	0.5438	26.43	0.761	0.1374	78.05	0.5720	0.6371	27.24	0.797	0.1024	65.46	0.6883	0.6880
	StableSR [29]	26.00	0.748	0.1962	118.77	0.5577	0.5627	26.93	0.790	0.1443	86.32	0.5861	0.5885	28.08	0.830	0.1200	67.13	0.6221	0.6043
	Ours	25.84	0.737	0.1673	100.97	0.6206	0.6020	26.77	0.782	0.1347	81.53	0.6310	0.6369	27.94	0.823	0.1006	64.19	0.6562	0.6660
Classic5 [34]	PromptIR [21]	33.14	0.935	0.1666	175.14	0.5745	0.5874	34.12	0.949	0.1367	119.13	0.6072	0.5983	35.53	0.961	0.1107	76.29	0.6359	0.6456
	PASD [32]	26.29	0.797	0.1311	81.19	0.5482	0.6633	27.89	0.816	0.1395	67.54	0.6003	0.6639	28.75	0.845	0.1112	55.69	0.6430	0.6661
	SUPIR [33]	27.23	0.791	0.1438	85.37	0.5752	0.6936	27.05	0.810	0.1533	71.86	0.6175	0.6944	28.42	0.839	0.1270	55.71	0.6534	0.6974
	RealESRGAN [30]	31.93	0.907	0.1133	75.30	0.5763	0.6894	32.60	0.918	0.0953	54.54	0.5808	0.6927	33.63	0.934	0.0940	53.91	0.6053	0.6943
	DiffBIR [17]	29.13	0.823	0.1438	84.36	0.6216	0.6405	29.79	0.833	0.1404	69.68	0.6115	0.6549	29.93	0.867	0.1221	55.19	0.6724	0.6772
	StableSR [29]	30.01	0.834	0.1325	87.77	0.5142	0.5490	30.43	0.844	0.1251	70.52	0.5592	0.5913	31.14	0.855	0.1238	55.23	0.5843	0.6065
	Ours	30.52	0.861	0.1189	82.38	0.6240	0.6824	30.87	0.866	0.1154	58.06	0.6290	0.6877	31.70	0.883	0.1119	47.62	0.6570	0.6958
BSDS500 [4]	PromptIR [21]	27.36	0.772	0.3334	201.01	0.3982	0.4065	28.44	0.820	0.2769	163.41	0.4651	0.4754	29.68	0.860	0.2714	111.36	0.5267	0.5385
	PASD [32]	26.22	0.740	0.2044	118.71	0.5341	0.5617	26.76	0.679	0.1426	94.36	0.5514	0.5890	27.18	0.813	0.1080	72.20	0.5757	0.6028
	SUPIR [33]	24.96	0.669	0.2021	118.41	0.5916	0.5344	25.60	0.676	0.1578	89.13	0.6444	0.6195	26.07	0.740	0.1161	71.11	0.6736	0.6608
	RealESRGAN [30]	26.54	0.748	0.3377	194.27	0.4050	0.4956	27.55	0.795	0.2712	148.01	0.4596	0.5612	28.33	0.831	0.2205	109.29	0.4972	0.6076
	DiffBIR [17]	25.86	0.718	0.2054	118.98	0.6155	0.6600	26.46	0.778	0.1402	95.18	0.6315	0.6655	27.68	0.775	0.1095	73.78	0.6521	0.6788
	StableSR [29]	26.91	0.744	0.2397	144.34	0.4673	0.5643	27.74	0.786	0.1852	106.26	0.5245	0.6115	28.79	0.825	0.1443	78.75	0.5681	0.6453
	Ours	27.04	0.753	0.1981	128.83	0.4824	0.5671	28.02	0.800	0.1318	87.31	0.5827	0.6175	29.20	0.841	0.1011	70.48	0.6142	0.6564
DIV2K [2]	PromptIR [21]	26.05	0.775	0.3402	193.12	0.3729	0.4534	27.18	0.825	0.2843	155.88	0.4019	0.4637	28.46	0.867	0.2468	121.26	0.4501	0.5245
	PASD [32]	25.19	0.698	0.1717	100.00	0.5495	0.5788	25.41	0.732	0.1289	86.99	0.5784	0.6166	26.09	0.744	0.1100	74.68	0.6038	0.6464
	SUPIR [33]	24.52	0.689	0.1527	104.39	0.4590	0.6202	24.82	0.724	0.1643	86.95	0.5575	0.6867	25.66	0.744	0.0961	78.68	0.6434	0.7031
	RealESRGAN [30]	25.50	0.743	0.2633	150.94	0.4493	0.5453	26.23	0.791	0.2030	107.19	0.5076	0.5936	27.08	0.825	0.1730	90.20	0.5342	0.6220
	DiffBIR [17]	25.40	0.708	0.1862	108.50	0.5758	0.5359	26.18	0.756	0.1290	88.64	0.5877	0.6187	26.94	0.781	0.0902	72.49	0.6411	0.6699
	StableSR [29]	25.41	0.742	0.1943	123.91	0.5618	0.5640	26.23	0.787	0.1468	91.69	0.5922	0.5805	27.30	0.829	0.1108	74.26	0.6104	0.5921
	Ours	24.97	0.724	0.1710	109.62	0.5862	0.5891	25.86	0.774	0.1281	81.16	0.6111	0.6193	27.08	0.822	0.0891	62.97	0.6437	0.6480
ICB [10]	PromptIR [21]	26.79	0.806	0.3208	241.54	0.2853	0.3201	27.89	0.844	0.2426	179.00	0.3123	0.3495	29.22	0.878	0.1994	135.15	0.3272	0.3498
	PASD [32]	26.17	0.674	0.2300	169.44	0.4932	0.5688	26.07	0.701	0.1590	117.98	0.5326	0.5888	27.19	0.744	0.1385	96.16	0.5420	0.6031
	SUPIR [33]	26.19	0.680	0.2000	172.96	0.4355	0.5287	26.12	0.690	0.1826	126.10	0.4989	0.6957	27.20	0.758	0.1699	101.97	0.5772	0.6603
	RealESRGAN [30]	26.86	0.789	0.2352	214.94	0.4015	0.5506	27.41	0.818	0.1904	158.37	0.4346	0.5940	27.87	0.839	0.1731	136.05	0.4574	0.6112
	DiffBIR [17]	26.38	0.773	0.1821	168.24	0.5107	0.6225	27.83	0.807	0.1245	118.92	0.4833	0.6569	29.20	0.839	0.0989	97.76	0.5303	0.6327
	StableSR [29]	27.26	0.791	0.1943	173.72	0.4404	0.5705	28.29	0.824	0.1488	118.92	0.4785	0.6108	29.30	0.858	0.1159	97.16	0.5138	0.6366
	Ours	27.16	0.780	0.1772	166.92	0.5312	0.5843	28.12	0.820	0.1226	111.74	0.5066	0.6163	29.31	0.858	0.0967	88.08	0.5428	0.6416

Table 8: Quantitative comparison for compressed image restoration on HIFIC [20] Codec with three distortion levels. Red and blue colors represent the best and second best performance, respectively.(Suggested to zoom in for better visualization.) *All comparison methods are reproduced on our constructed CIR datasets except for SUPIR [33].*

Dataset	Methods	HIFIC																	
		Mode = 'Low'						Mode = 'Med'						Mode = 'High'					
		PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA	PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA	PSNR	SSIM	LPIPS	FID	ClipIQA	ManIQA
LIVE1 [23]	PromptIR [21]	28.39	0.827	0.1453	96.45	0.4182	0.4987	30.07	0.882	0.1206	83.83	0.4691	0.5093	31.22	0.920	0.0959	68.15	0.5185	0.5374
	PASD [32]	27.38	0.776	0.0866	62.65	0.6741	0.6676	28.22	0.799	0.0674	51.52	0.6700	0.6862	28.39	0.828	0.0510	37.93	0.6860	0.7091
	SUPIR [33]	27.23	0.712	0.1004	65.20	0.7067	0.6677	27.91	0.756	0.0664	47.28	0.6573	0.7048	28.28	0.776	0.0538	32.73	0.6876	0.7039
	RealESRGAN [30]	27.59	0.793	0.0992	69.63	0.6396	0.6496	29.18	0.855	0.0740	54.64	0.6285	0.6653	29.82	0.900	0.0565	36.13	0.6477	0.6884
	DiffBIR [17]	27.37	0.777	0.0772	59.16	0.6765	0.6812	28.27	0.812	0.0669	46.10	0.7323	0.7063	28.44	0.826	0.0443	30.15	0.7116	0.7175
	StableSR [29]	27.43	0.782	0.0949	62.76	0.6272	0.6006	29.34	0.850	0.0661	44.10	0.6405	0.6059	29.84	0.892	0.0507	33.20	0.6533	0.6130
	Ours	27.62	0.788	0.0759	56.04	0.6776	0.6718	29.60	0.855	0.0591	44.72	0.6787	0.6889	30.31	0.898	0.0430	29.99	0.6983	0.7105
Classic5 [34]	PromptIR [21]	31.62	0.902	0.1049	78.14	0.6664	0.6693	32.91	0.919	0.0928	60.17	0.6970	0.6873	33.53	0.933	0.0896	54.21	0.6723	0.6898
	PASD [32]	25.20	0.795	0.0865	47.02	0.6445	0.6526	27.99	0.826	0.0720	40.81	0.6657	0.6607	29.02	0.834	0.0685	33.89	0.6061	0.6699
	SUPIR [33]	25.52	0.790	0.0976	50.22	0.6724	0.6937	27.86	0.819	0.0717	44.13	0.7008	0.6960	28.91	0.828	0.0705	38.35	0.6353	0.7009
	RealESRGAN [30]	27.55	0.900	0.0937	57.17	0.6395	0.6503	28.06	0.926	0.0823	47.51	0.6372	0.6701	28.96	0.929	0.0761	38.82	0.6453	0.6716
	DiffBIR [17]	27.49	0.830	0.0824	47.78	0.6371	0.6639	28.70	0.852	0.0783	41.76	0.6809	0.6716	29.97	0.866	0.0725	35.37	0.7088	0.6746
	StableSR [29]	28.54	0.866	0.0790	42.91	0.5696	0.6757	29.89	0.877	0.0833	39.35	0.5764	0.6808	30.90	0.887	0.0753	35.55	0.5891	0.6944
	Ours	30.31	0.859	0.0856	41.62	0.6600	0.6859	32.01	0.886	0.0749	35.05	0.6727	0.6891	32.67	0.895	0.0697	31.00	0.6739	0.6979
BSDS500 [4]	PromptIR [21]	26.93	0.802	0.1589	91.55	0.4702	0.4873	28.28	0.863	0.1316	78.91	0.5162	0.5232	29.14	0.908	0.1071	67.24	0.5886	0.5993
	PASD [32]	26.73	0.739	0.1021	84.03	0.6063	0.6003	27.59	0.796	0.0957	69.47	0.6096	0.6044	28.24	0.827	0.0559	43.60	0.6151	0.6113
	SUPIR [33]	26.41	0.700	0.1168	81.70	0.7154	0.6536	27.38	0.738	0.1137	66.74	0.7215	0.6801	28.32	0.829	0.0759	42.57	0.7873	0.6907
	RealESRGAN [30]	25.89	0.755	0.1230	85.44	0.5995	0.6222	26.85	0.822	0.1026	69.57	0.5959	0.6381	27.53	0.876	0.0863	57.54	0.6022	0.6592
	DiffBIR [17]	26.15	0.761	0.1105	88.86	0.6719	0.6163	26.44	0.807	0.1032	72.43	0.7009	0.6491	26.80	0.818	0.0623	46.81	0.7160	0.6860
	StableSR [29]	25.98	0.744	0.1115	79.37	0.6503	0.6490	27.27	0.815	0.0858	60.88	0.6546	0.6670	27.62	0.861	0.0741	49.32	0.6795	0.6904
	Ours	26.33	0.758	0.0983	68.99	0.6807	0.6536	27.83	0.832	0.0726	51.78	0.6930	0.6729	28.45	0.883	0.0549	40.33	0.7280	0.6917
DIV2K [2]	PromptIR [21]	27.25	0.826	0.1421	93.81	0.4304	0.4987	29.32	0.886	0.1138	79.24	0.4675	0.5192	30.62	0.924	0.0900	65.70	0.5217	0.5764
	PASD [32]	26.72	0.703	0.0974	72.67	0.6642	0.6492	27.68	0.739	0.0598	54.91	0.6719	0.6698	28.36	0.761	0.0439	48.30	0.6918	0.6920
	SUPIR [33]	26.23	0.692	0.1350	75.62	0.7100	0.6818	27.05	0.743	0.0709	58.42	0.7271	0.7004	28.22	0.764	0.0444	52.06	0.7456	0.7068
	RealESRGAN [30]	26.43	0.786	0.1148	77.29	0.6230	0.6244	27.61	0.841	0.1019	67.31	0.6224	0.6394	28.81	0.890	0.0779	55.05	0.6417	0.6637
	DiffBIR [17]	26.63	0.766	0.0947	72.54	0.6591	0.6680	27.04	0.798	0.0767	55.63	0.7050	0.6909	27.73	0.825	0.0629	49.03	0.6803	0.7014
	StableSR [29]	26.16	0.780	0.0930	69.76	0.6317	0.5923	27.72	0.846	0.0654	50.70	0.6383	0.5970	28.58	0.884	0.0532	39.97	0.6457	0.6010
	Ours	26.50	0.787	0.0876	65.86	0.6768	0.6503	28.30	0.857	0.0589	45.42	0.6834	0.6692	29.45	0.899	0.0420	34.43	0.6999	0.6905
ICB [10]	PromptIR [21]	29.06	0.864	0.1983	160.14	0.3172	0.4876	29.63	0.888	0.1638	107.86	0.3289	0.4395	31.89	0.933	0.1110	100.45	0.3666	0.4389
	PASD [32]	26.12	0.729	0.1467	106.28	0.5660	0.5991	27.18	0.756	0.0836	68.14	0.5529	0.6047	27.39	0.801	0.1188	62.16	0.5600	0.6138
	SUPIR [33]	26.17	0.733	0.1172	108.69	0.6014	0.6513	27.22	0.771	0.0878	73.19	0.6953	0.7036	27.40	0.802	0.0758	68.54	0.6059	0.7130
	RealESRGAN [30]	28.77	0.848	0.1191	124.53	0.4932	0.6156	29.18	0.868	0.1101	101.73	0.4949	0.6284	30.24	0.909	0.0749	86.07	0.5486	0.6528
	DiffBIR [17]	28.39	0.814	0.0958	105.30	0.5613	0.6267	29.50	0.842	0.0741	66.76	0.5358	0.6017	29.56	0.859	0.0628	66.20	0.5398	0.6675
	StableSR [29]	28.46	0.834	0.1034	112.03	0.5592	0.6326	29.86	0.872	0.0847	79.55	0.5495	0.6545	30.06	0.895	0.0746	65.19	0.5996	0.6739
	Ours	29.04	0.839	0.0861	97.85	0.5691	0.6414	30.22	0.876	0.0675	70.02	0.5498	0.6594	31.28	0.911	0.0519	54.48	0.6104	0.6804

Fig. 3: Visual comparisons of our MoE-DiffIR with other SOTA models on codec VTM(QP=47).

Fig. 4: Visual comparisons of our MoE-DiffIR with other SOTA models on codec C_{PNSR}(Q=3).

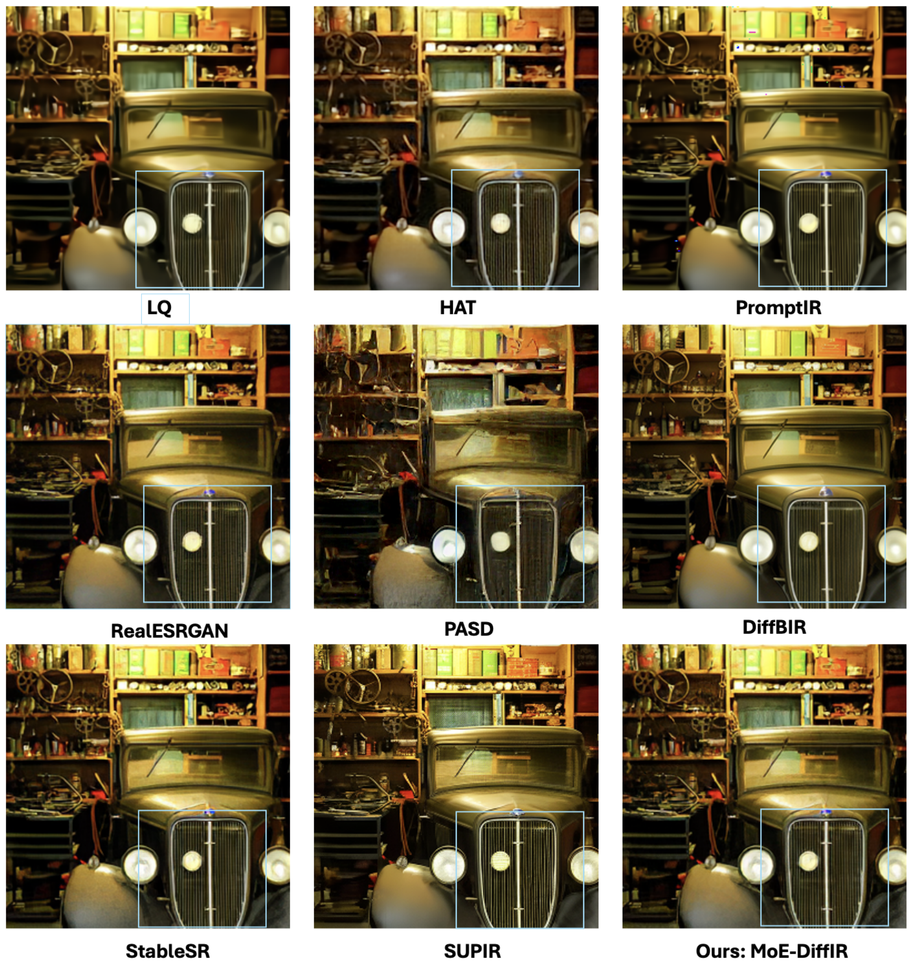

Fig. 5: Visual comparisons of our MoE-DiffIR with other SOTA models on codec HM(QP=37).

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