

Supplementary Materials: D³U-Net: Dual-Domain Collaborative Optimization Deep Unfolding Network for Image Compressive Sensing

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1 Overview

In this supplementary material, we present additional experimental results and visual analysis not included in our main manuscript due to space limitations. Moreover, the structure of the RFF block within the WDM is depicted in Fig. 2. The RFF block is employed to refine the information from the previous stage, which can extract essential features and eliminate redundant information. It facilitates inter-stage information exchange and enhances the reconstruction capabilities of the current stage in effect.

2 More Experimental Details and Analysis

This section presents additional comparative results that highlight the performance of our proposed method, D³U-Net, against other superior methods. Table 1 provides the average PSNR/SSIM comparisons across different sampling rates for our D³U-Net and other advanced methods on various benchmark datasets. For example, our D³U-Net outperforms AMP-Net [8], COAST-Net [6], ISTA-Net++ [5], MADUN [1], DPUNet [4], DPC-DUN [2], SODAS-Net [3] by 1.86 dB, 2.52 dB, 4.89 dB, 3.77 dB, 2.01 dB, 1.61 dB, 1.97 dB, and 2.56 dB in terms of PSNR on General100 dataset when the CS sampling ratio is 10%, respectively. In addition, the average SSIM gain of our method over these comparison methods is 0.0233, 0.0469, 0.1031, 0.0728, 0.0382, 0.0162, 0.0342, and 0.0456, respectively. As shown in Fig. 1 and Fig. 4, visual comparisons are conducted on three natural benchmark images named “foreman” from Set14, and “bird”, “head” from Set5 at a 10% CS sampling ratio, which can be seen that our method can recover much clearer edges and textures than other methods. Compared to COAST-Net [6], ISTA-Net++ [5], MADUN [1], and AMP-Net [8], our method achieved improvements of 2.41 dB, 1.49 dB, 2.12 dB, and 2.65 dB in terms of PSNR on the benchmark image named “foreman” from Set14 when the CS sampling ratio is 10%, respectively.

3 The Visual Analysis of Dual-main Information

In this section, we further analyze the impact of dual-domain information, where the visual analysis of the feature maps provides a deeper insight. The visual maps in Fig. 3 illustrate that our Image Domain Mapping (IDM) and Wavelet Domain Mapping (WDM) blocks focus on different aspects of information and are mutually complementary. As shown in Fig. 3, the color change from blue to red shows a shift in attention levels, in which cooler blues indicate less attention. Conversely, the transition to a warm red represents a significant increase in attention, denoting improved levels of cognitive engagement. The sub-figure 3a highlights the regions of interest for the difference block, while sub-figure 3b identifies the areas of concern for the consistency block. And sub-figure 3c illustrates the areas of concern by only utilizing wavelet domain

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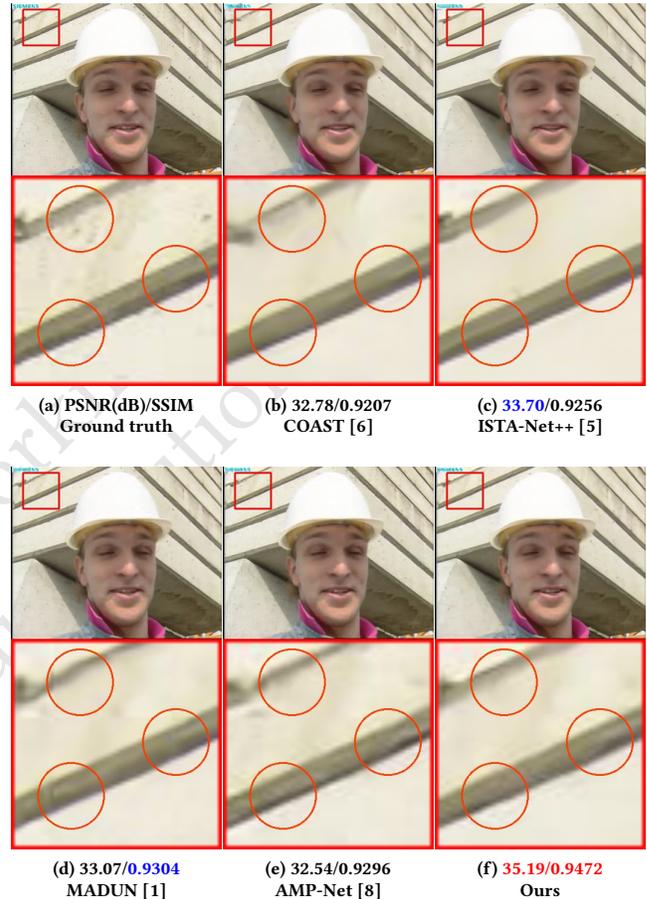


Figure 1: Visual quality comparisons between our MTADUN and recently state-of-the-art CS methods on Set14 at 10% CS sampling ratio. The best and second-best results are highlighted in red and blue, respectively.

information, which focuses on preserving more details and edges. In contrast, sub-figure 3d depicts the areas of concern only using image domain information, which pays more attention to smooth regions. They indicate that information from different domains can be complementary to each other. The final sub-figure 3e shows that our D³U-Net is capable of focusing on a broader range of information, demonstrating enhanced sensitivity to details with increased fidelity. This indicates that introducing information from different domains contributes to recovering superior images.

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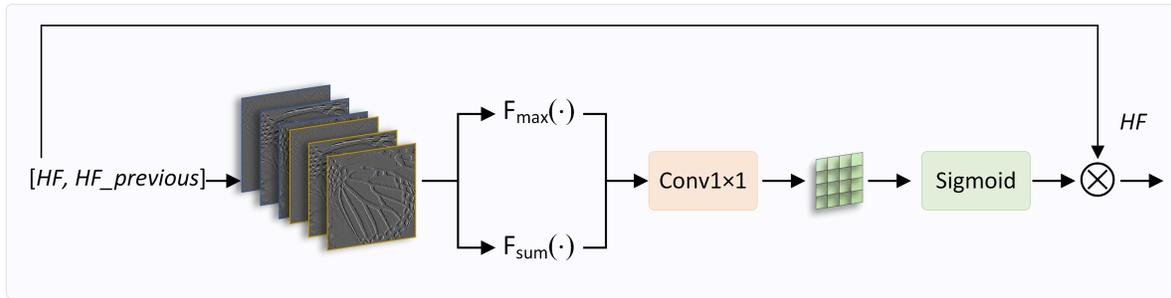


Figure 2: The structure of the RFF block.

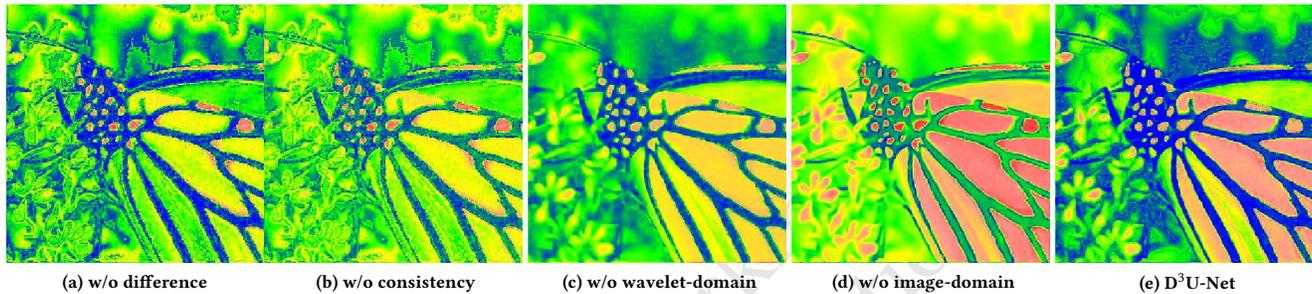


Figure 3: Visual analysis of feature maps at the ninth stage of our D^3U -Net. It shows that introducing dual-domain information enables the network to pay more high-fidelity attention to details. The color change from blue to red shows a shift in attention levels, in which cooler blues indicate less attention. Conversely, the transition to a warm red represents a significant increase in attention, denoting improved levels of cognitive engagement.

Table 1: Average PSNR(dB)/SSIM comparisons with different methods. The best and second-best results are highlighted in bold and underlined, respectively.

Dataset	Method	Sampling Rate				
		10%	20%	30%	40%	50%
Set14	AMP-Net [8]	28.69/0.8171	31.95/0.8933	34.27/0.9293	36.26/0.9505	38.10/0.9647
	COAST [6]	27.41/0.7799	30.71/0.8672	33.10/0.9106	35.12/0.9369	36.93/0.9549
	ISTA-Net [7]	25.85/0.7214	28.91/0.8289	31.37/0.8868	33.48/0.9221	35.60/0.9450
	ISTA-Net++ [5]	26.75/0.7549	30.09/0.8518	32.40/0.8999	34.26/0.9287	35.90/0.9477
	MADUN [1]	27.97/0.7914	31.50/0.8790	34.05/0.9194	36.05/0.9439	37.96/0.9592
	DPUNet [4]	28.49/0.8226	31.61/0.8963	33.95/0.9308	35.93/0.9505	37.66/0.9628
	DPC-DUN [2]	28.02/0.7947	31.37/0.8781	33.92/0.9188	35.91/0.9429	37.83/0.9592
	SODAS-Net [3]	27.54/0.7812	30.32/0.8624	33.62/0.9163	35.72/0.9415	37.61/0.9581
	Ours	29.75/0.8419	33.07/0.9096	35.52/0.9403	37.49/0.9580	39.50/0.9699
General100	AMP-Net [8]	31.28/0.8825	35.29/0.9401	38.02/0.9645	40.11/0.9771	41.96/0.9848
	COAST [6]	30.62/0.8589	34.39/0.9238	36.91/0.9520	39.04/0.9681	40.95/0.9783
	ISTA-Net [7]	28.25/0.8027	31.94/0.8920	34.90/0.9350	37.25/0.9572	39.36/0.9716
	ISTA-Net++ [5]	29.37/0.8330	33.14/0.9110	35.69/0.9443	37.74/0.9626	39.44/0.9736
	MADUN [1]	31.13/0.8676	35.15/0.9329	37.86/0.9594	40.08/0.9735	42.18/0.9821
	DPUNet [4]	31.53/0.8896	35.41/0.9430	38.04/0.9650	40.16/0.9767	41.94/0.9836
	DPC-DUN [2]	31.17/0.8716	34.98/0.9321	37.76/0.9590	39.95/0.9731	42.01/0.9820
	SODAS-Net [3]	30.58/0.8602	34.10/0.9224	37.49/0.9576	39.74/0.9722	41.74/0.9813
	Ours	33.14/0.9058	36.99/0.9522	39.71/0.9716	41.91/0.9818	44.22/0.9885

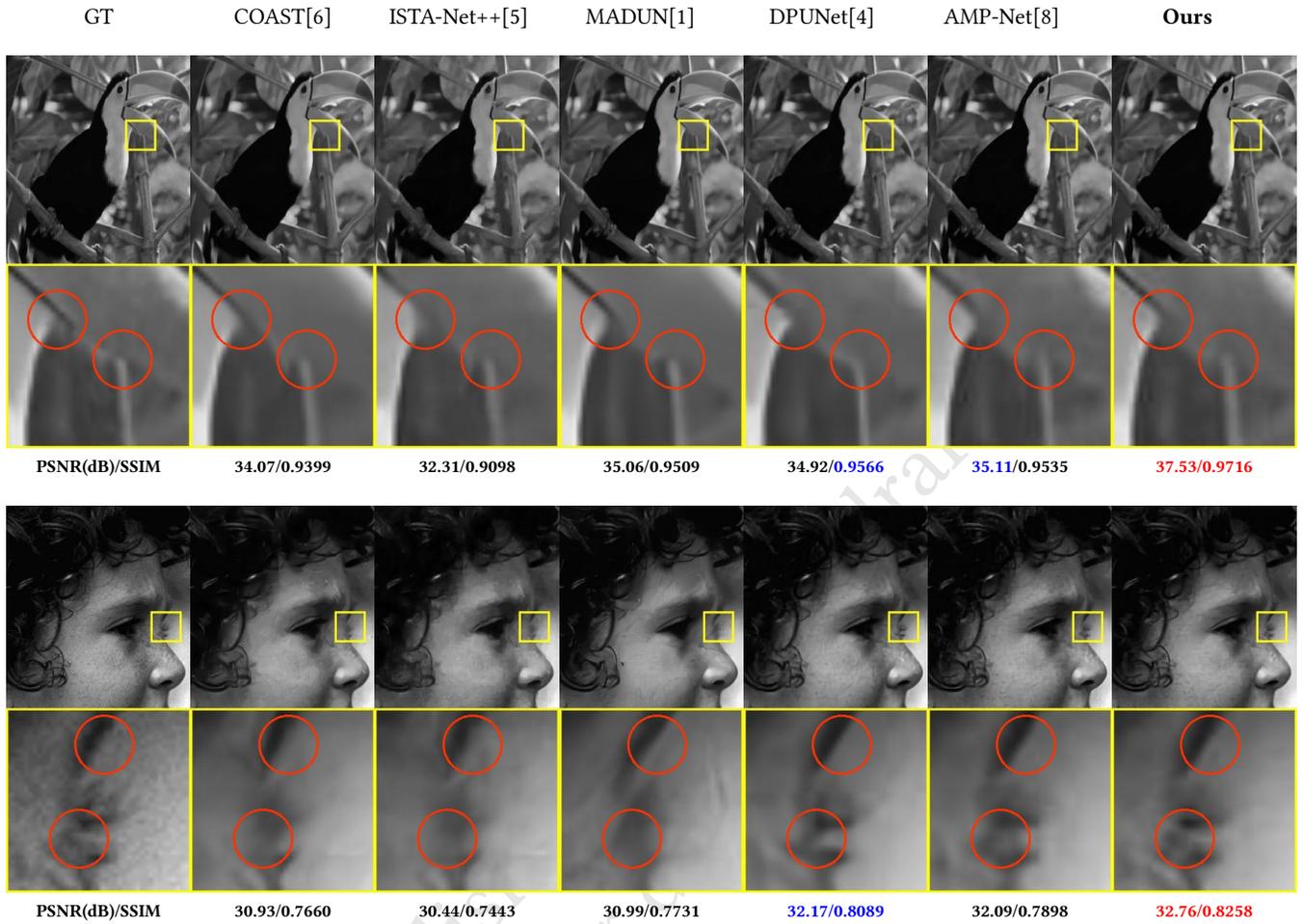


Figure 4: Visual quality comparisons between our proposed method and recently state-of-the-art CS methods on Set5 at 10% CS sampling ratio. The best and second-best results are highlighted in red and blue, respectively.

References

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