Overcoming Distribution Mismatch in Quantizing Image Super-Resolution Networks

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Paper under double-blind review

In this supplementary material, we present the implementation details of our training framework, ODM in Section S1; additional experimental results in Section S2; additional ablation study in Section S3; additional qualitative results in Section S4; additional analyses in Section S5.

S1 Implementation details

λ_V, the balance weight between reconstruction loss and variance regularization loss, is set differently based on the backbone model. We set λ_V, as 1×10^{-4} for EDSR and SRResNet, and 1×10^{-5} for RDN, which is a larger model with more convolutional layers than EDSR and SRResNet. Since $\mathcal{L}_V$ is sum of the variances in features of all the convolutional layers, it is natural to leverage smaller λ_V for larger models.

S2 Additional experiments

In addition to the evaluations done in the main manuscript on representative SR networks, we evaluate our framework on lightweight SR models. As shown in Table S1, our framework achieves consistent gain over existing methods in both CARN (Ahn et al., 2018) and SwinIR (Liang et al., 2021) backbones.

Model	Bit	Set5	Set14	B100	Urban100
CARN	32	32.14	28.61	27.58	26.07
CARN-PAMS	4	31.17	28.00	27.16	25.08
CARN-DDTB	4	31.70	28.30	27.37	25.54
CARN-ODM (Ours)	4	**31.91**	**28.42**	**27.47**	**25.79**
SwinIR-light	32	32.44	28.77	27.69	26.47
SwinIR-light-PAMS	4	31.99	28.50	27.49	25.86
SwinIR-light-DDTB	4	32.09	28.55	27.54	26.01
SwinIR-light-ODM (Ours)	4	**32.21**	**28.63**	**27.58**	**26.18**

Table S1: **Evaluation on CARN and SwinIR-light** of scale 4. For fair comparison, each quantized model is updated for 60 epochs

Also, along with the results of the main manuscript done on SR networks of scale $\times 4$, we evaluate our framework on networks of scale $\times 2$. As shown in Table S2, our framework outperforms existing SR quantization methods in terms of both PSNR and SSIM, demonstrating the effectiveness of our approach on scale 2 SR networks. Specifically, the PSNR gain on Set5 is 0.37 dB on EDSR and 0.37 dB on RDN, while it is 0.06 dB on SRResNet, as the distribution mismatch problem is particularly trivial for SRResNet.

Moreover, we compare our method with fully-quantized SR networks, EDSR-FQSR [40], which quantizes all layers and also the skip-connections. To make a fair comparison, we also quantize all convolutional layers and the skip-connetions. In Table S3, the results demonstrate that ODM is also effective when the network is fully quantized.

Model	Bit	Set5		Set14		B100		Urban100	
		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
EDSR	32	37.93	0.960	33.46	0.916	32.10	0.899	31.71	0.925
EDSR-PAMS	2	35.30	0.946	31.63	0.899	30.66	0.879	28.11	0.875
EDSR-DDTB	2	37.25	0.958	32.87	0.911	31.67	0.893	30.34	0.910
EDSR-ODM (Ours)	2	**37.62**	**0.959**	**33.14**	**0.914**	**31.88**	**0.896**	**30.92**	**0.917**
RDN	32	38.05	0.961	33.59	0.917	32.20	0.900	32.13	0.927
RDN-PAMS	2	35.45	0.946	31.67	0.899	30.69	0.879	28.14	0.874
RDN-DDTB	2	36.76	0.955	32.54	0.908	31.44	0.890	29.77	0.903
RDN-ODM (Ours)	2	**37.13**	**0.957**	**32.69**	**0.910**	**31.53**	**0.892**	**29.92**	**0.904**
SRResNet	32	37.89	0.960	33.40	0.916	32.08	0.898	31.60	0.923
SRResNet-PAMS	2	34.75	0.942	31.31	0.896	30.48	0.877	27.86	0.868
SRResNet-DDTB	2	37.46	0.958	33.02	0.913	31.78	0.895	30.57	0.913
SRResNet-ODM (Ours)	2	**37.52**	**0.959**	**33.02**	**0.913**	**31.79**	**0.895**	**30.55**	**0.913**

Table S2: **Quantitative comparisons on SR networks of scale $\times 2$.**

Scale	Model	Bit	S.C.	Set5		Set14		B100		Urban100	
				PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
$\times 4$	EDSR [33]	32	32	32.10	0.894	28.58	0.781	27.56	0.736	26.04	0.785
	EDSR-FQSR [40]	4	8	30.93	0.870	27.82	0.761	27.07	0.715	24.93	0.744
	EDSR-DDTB [48]	4	8	31.91	0.889	28.40	0.777	27.44	0.732	25.70	0.775
	EDSR-ODM (Ours)	4	8	**32.02**	**0.891**	**28.46**	**0.778**	**27.48**	**0.734**	**25.76**	**0.777**
$\times 2$	EDSR [33]	32	32	37.93	0.960	33.46	0.916	32.10	0.899	31.71	0.925
	EDSR-FQSR [40]	4	8	37.04	0.951	32.84	0.908	31.67	0.889	30.65	0.911
	EDSR-DDTB [48]	4	8	37.83	0.960	33.44	0.916	32.07	0.898	31.60	0.924
	EDSR-ODM (Ours)	4	8	**37.87**	**0.960**	**33.43**	**0.915**	**32.10**	**0.899**	**31.75**	**0.925**

Table S3: **Quantitative comparisons on EDSR with fully quantized methods.** S.C. refers to the bit-width of skip-connections.

S3 Additional ablation study

According to the ablation on offset ratio p of Table S4a, we found that 0.3 is a reasonable value among different ratios. This is because as larger p gives minimal or no accuracy gain but at the cost of additional parameters. Also, for ablation on the balancing weight λ in Table S4b, we follow PAMS and DDTB for using 1000. Nevertheless, we added ablations on different λ values. The results justify our selection on 1000 as the balancing weight.

p	Set5	Set14	B100	Urban100
0.1	31.48	28.11	27.26	25.14
0.3	31.49	28.12	27.26	25.15
0.5	31.47	28.13	27.27	25.17
1.0	31.49	28.16	27.27	25.17

(a) Ablation on p

λ	Set5	Set14	B100	Urban100
10	31.44	28.11	27.26	25.14
100	31.46	28.11	27.26	25.14
1000	31.49	28.12	27.26	25.15

(b) Ablation on λ

Table S4: **Ablation on hyperparameters** on EDSR $\times 4$ (2-bit).

S4 Additional qualitative results

We show more visual comparisons in Figure S1. Overall, while other methods suffer from blurred lines or damaged structures in test images (Urban100), our approach produces further clear lines and structures. These results demonstrate that our ODM is beneficial quantitatively and qualitatively.

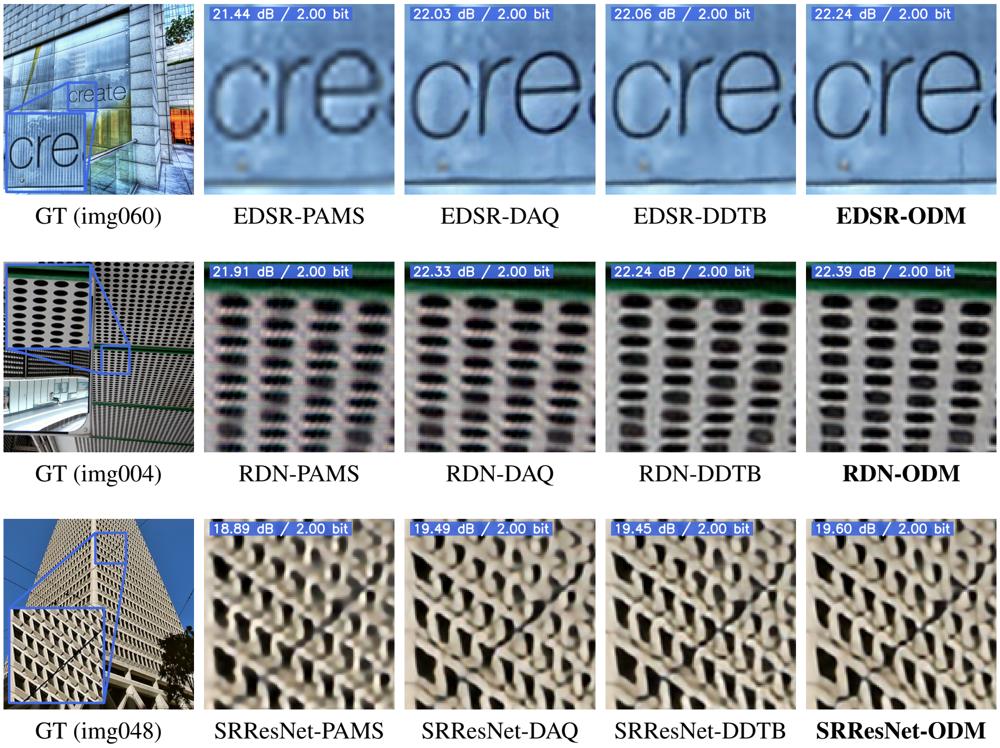


Figure S1: **Qualitative results** on EDSR, RDN, and SRResNet of scale 4.

S5 Additional analyses

S5.1 Distribution mismatch

The distribution mismatch problem is especially severe for SR networks. For example, as reported in Table S5, the classification network (ResNet20) shows a much more minor image-wise and channel-wise distribution mismatch compared to SR networks (EDSR, RDN).

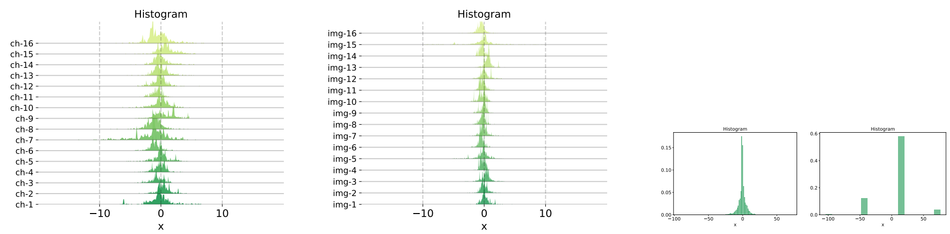
Model	Image-wise Variance	Channel-wise Variance
EDSR ($\times 4$)	15.08	40.29
RDN ($\times 4$)	6.40	58.14
ResNet-20	0.04	0.09

Table S5: **Average feature mismatch** on EDSR, RDN $\times 4$, and ResNet-20. The metrics are measured on DIV2K validation set for SR networks and ImageNet validation set for the classification network.

Also, we visualize the distribution mismatch after using our framework, ODM, before and after quantization. Figure S2 demonstrates that ODM effectively reduces the distribution mismatch, pushing the network towards a quantization-robust grid.

S5.2 Gradient conflict

We define gradient conflict when the sign of gradient from reconstruction loss and that of regularization is the opposite. In the main manuscript, we disregard the gradient of regularization when the two gradients conflict. Instead of disregarding the gradient of the regularization when the two gradients conflict, we added analysis for weighting the regularization loss by the degree of conflict between two losses (measured by the cosine similarity). According to the results in Table S6, it was slightly better to disregard the variance regularization loss when it is not cooperative.



(a) Channel-wise features (b) Image-wise features (c) Before/After quantization

Figure S2: **Distribution mismatch after ODM is applied.** Visualization done on EDSR ($\times 4$). Channels and images of a layer are randomly selected for visualization. Also, we plot the feature distribution of the second layer of EDSR before and after quantization (2-bit).

Method	Set5	Set14	B100	Urban100
VR disregarded when $\nabla_\theta L_R \cdot \nabla_\theta L_V < 0$	31.49	28.12	27.26	25.15
VR weighted with $cos(\nabla_\theta L_R, \nabla_\theta L_V)$	31.45	28.12	27.25	25.14

Table S6: **Analysis on the degree of gradient conflict** on EDSR $\times 4$ (2-bit). VR denotes the variance regularization and $cos()$ measures cosine similarity.

License of the Used Assets

- DIV2K [1] dataset is publicly available for academic research purposes.
- Set5 [4], Set14 [29], BSD100 [37], Urban100 [19] datasets are made available at `https://github.com/jbhuang0604/SelfExSR`.

References

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