Supplementary Material for Fully Quantized Image Super-Resolution Networks

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CCS CONCEPTS

• **Computing methodologies** → **Computer Vision**; • **Image processing**; • **Reconstruction**;

KEYWORDS

Image Super-resolution, Model Quantization, Computational Cost, Memory Consumption

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1 VISUALIZATION OF SUPER-RESOLUTION IMAGES

The visualization of super-resolution images are shown in Figure 1 and Figure 2. The figure shows that the proposed FQSR models (8/8/8 model) are able to receive much better results than the bicubic method and comparable results with the full-precision models.

2 EQUIP FQSR ON RCAN

We have further conducted experiments to perform our FQSR on the RCAN model[4], as shown by Table 1.

Similar to the quantitative results shown on SRResNet, EDSR and SRGAN models, our FQSR (8/8/8) model receives comparable PSNR and SSIM results with its full-precision model. On B100 and Urban100 dataset, the 8/8/8 FQSR model can outperform its full-precision version.

3 EXPERIMENTAL RESULTS WITH SELF-ENSEMBLE

Follow the evaluation of EDSR model [2], in this section, we present the model performance with self-ensemble [3]. The results generally show that with self-ensemble, the model performance can be further boosted.

Self-ensemble [3] Self-ensemble is a strategy for SR model to further enhance the performance. During the testing phase, after rotating an input image at multiple angles, seven augmented images are obtained. By inputting the set of images into the model, the corresponding super-resolution images are obtained as well. Then, these super-resolution images are rotated back to the original angle. The final super-resolution image is obtained by weight-averaging these eight images (including the identity image).

Evaluation on SRResNet [1] As shown in Table 2, when compared to the Bicubic interpolation, the performance of 4/4/8 model can surpass it by a large margin. 6/6/6, 6/6/8 models are able to receive comparable results with the full-precision models. 8/8/8 and 8/8/32 models can achieve better results than the full-precision models in most of the metrics and datasets. The lite version 6/6/8 model is able to outperform the normal 6/6/8 model with fewer computation requirements and memory consumption.

Evaluation on EDSR [2] Table 3 shows the model performance on the EDSR structure. Similar as shown in Table 2, the 4/4/8 model is able to achieve much better performance than the Bicubic interpolation. The table generally similar results as the model without self-ensemble. The 6/6/6 version model can boost the performance significantly from 4/4/8 and 4/4/32. The 8/8/8 and 8/8/32 models can outperform the full-precision model in most cases.

Evaluation on SRGAN [1] Table 4 shows the model performance on the SRGAN structure. When compared to Bicubic interpolation, the performance of 4/4/8 model can outperform it significantly. Surprisingly, the 6/6/8 models surpass or receive comparable results to the full-precision models in multiple datasets and metrics.

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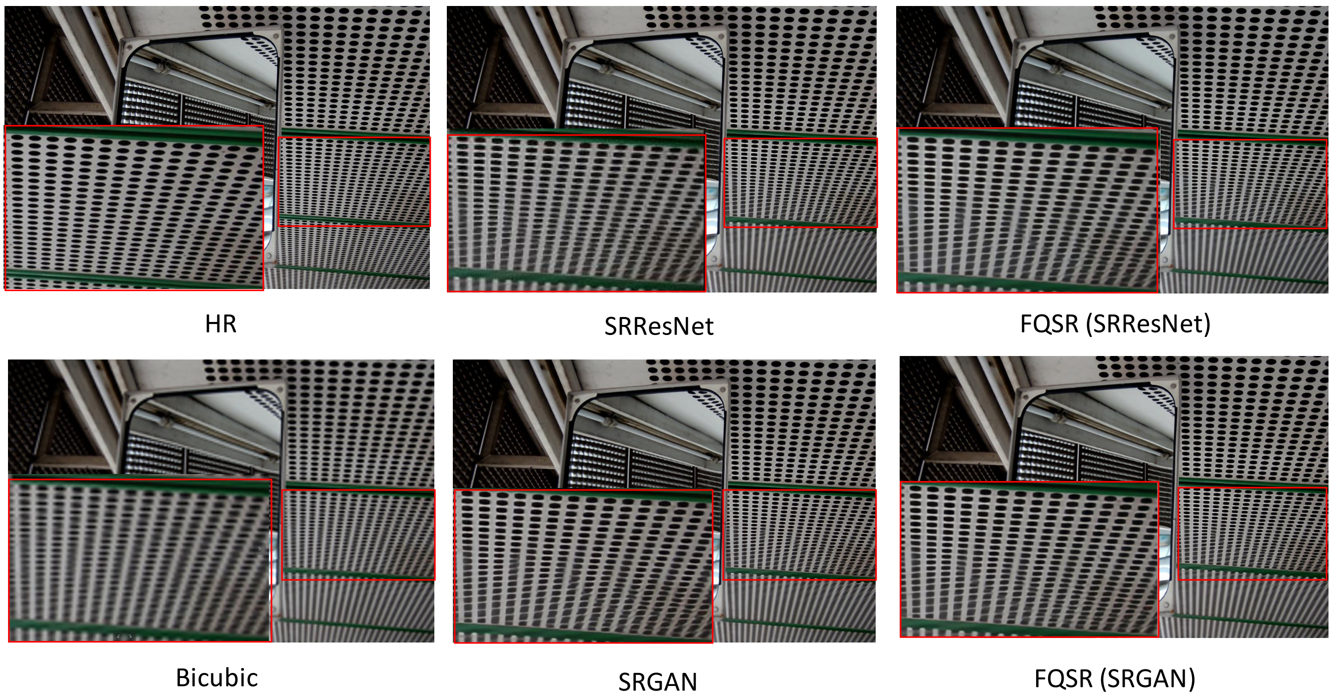

Figure 1: The visualization of Super-resolution images on $\times 4$ up-scaling. The SRResNet and SRGAN models denote full-precision models; the FQSR (SRResNet) and FQSR (SRGAN) models represent the 8/8/8 models on SRResNet and SRGAN respectively. As shown in the figure, the proposed FQSR models are able to achieve much better results than the bicubic method and comparable results with the full-precision models. The red box areas are the areas to be zoomed.

Table 1: The comparison of our FQSR with full-precision networks on RCAN.

Methods	Scale	wt	fm	sc	Set5		Set14		B100		Urban100		DIV2K	
					PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
RCAN	$\times 2$	32	32	32	38.103	0.959	33.787	0.917	32.155	0.898	32.058	0.927	34.800	0.946
FQSR (Ours)	$\times 2$	8	8	8	38.063	0.959	33.637	0.917	32.225	0.898	32.436	0.930	34.650	0.945

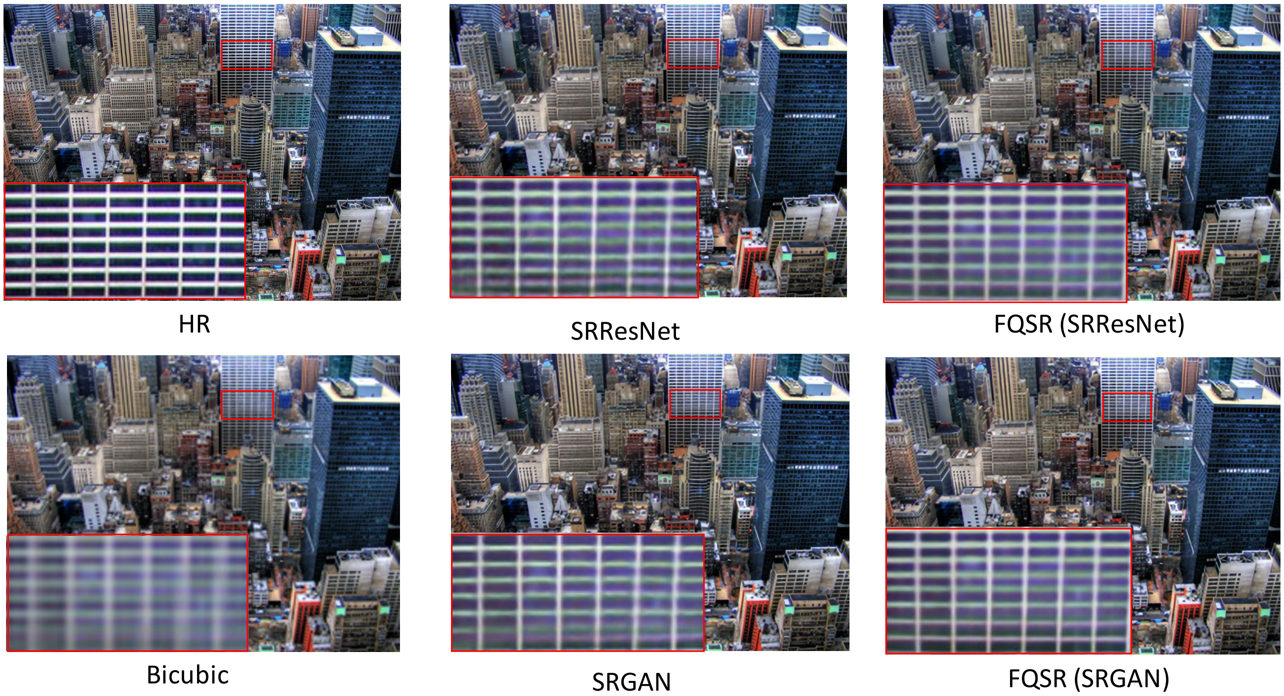

Figure 2: Another visualization of Super-resolution images on $\times 4$ up-scaling. As shown in the figure, the proposed FQSR models are able to achieve much better results than the bicubic method and comparable results with the full-precision models. The red box areas are the areas to be zoomed.

Table 2: The comparison of our FQSR with full-precision networks on SRResNet with self-ensemble. The star signs represent models equipped with self-ensemble.

Methods	Scale	wt	fm	sc	Set5		Set14		B100		Urban100		DIV2K	
					PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
SRResNet* [1]	×2	32	32	32	37.802	0.958	33.28	0.914	31.993	0.895	31.162	0.917	34.193	0.941
Bicubic	×2	32	32	32	33.660	0.930	30.240	0.869	29.56	0.843	26.880	0.84	31.010	0.939
	×2	4	4	8	37.099	0.955	32.752	0.91	31.646	0.891	30.253	0.908	33.018	0.937
	×2	4	4	32	37.457	0.957	32.967	0.912	31.792	0.893	30.675	0.913	33.507	0.939
	×2	6	6	6	37.703	0.957	33.285	0.913	32.021	0.895	31.413	0.92	34.019	0.941
FQSR* (Ours)	×2	6	6	8	37.838	0.958	33.389	0.915	32.085	0.896	31.589	0.896	34.235	0.942
	×2	8	8	8	37.796	0.959	33.328	0.916	32.049	0.897	31.556	0.923	33.634	0.943
	×2	8	8	32	37.995	0.959	33.508	0.916	32.15	0.897	31.85	0.925	34.542	0.944
FQSR_Lite* (Ours)	×2	6	6	8	37.673	0.958	33.249	0.913	31.97	0.895	31.16	0.918	34.051	0.941
SRResNet* [1]	×4	32	32	32	32.106	0.892	28.567	0.778	27.552	0.73	25.919	0.777	28.891	0.834
Bicubic	×4	32	32	32	28.420	0.810	26.000	0.703	25.960	0.668	23.140	0.658	26.66	0.852
	×4	4	4	8	31.328	0.88	28.035	0.765	27.198	0.718	25.077	0.749	28.179	0.82
	×4	4	4	32	31.613	0.885	28.213	0.771	27.299	0.722	25.294	0.758	28.306	0.825
	×4	6	6	6	32.026	0.891	28.464	0.778	27.502	0.73	25.832	0.777	28.687	0.833
FQSR* (Ours)	×4	6	6	8	32.102	0.892	28.509	0.778	27.523	0.729	25.884	0.777	28.729	0.833
	×4	8	8	8	32.037	0.891	28.488	0.776	27.51	0.728	25.839	0.774	28.487	0.832
	×4	8	8	32	32.25	0.894	28.633	0.782	27.611	0.733	26.149	0.786	28.998	0.837
FQSR_Lite* (Ours)	×4	6	6	8	31.854	0.889	28.369	0.775	27.423	0.727	25.571	0.768	28.579	0.829

Table 3: The comparison of our FQSR with full-precision networks on EDSR with self-ensemble.

Methods	Scale	wt	fm	sc	Set5		Set14		B100		Urban100		DIV2K	
					PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
EDSR* [2]	×2	32	32	32	38.014	0.959	33.564	0.916	32.188	0.898	32.009	0.926	34.620	0.944
Bicubic	×2	32	32	32	33.660	0.930	30.240	0.869	29.560	0.843	26.880	0.840	31.010	0.939
FQSR* (Ours)	×2	4	4	8	37.707	0.957	33.124	0.913	31.914	0.894	30.872	0.917	33.907	0.941
	×2	4	4	32	37.726	0.958	33.161	0.913	31.938	0.895	30.922	0.917	33.962	0.941
	×2	6	6	6	37.954	0.959	33.431	0.915	32.120	0.896	31.672	0.923	34.356	0.943
	×2	6	6	8	38.044	0.959	33.527	0.916	32.181	0.898	31.929	0.926	34.541	0.945
	×2	8	8	8	38.075	0.959	33.611	0.917	32.213	0.898	32.162	0.928	34.677	0.945
	×2	8	8	32	38.084	0.959	33.645	0.917	32.221	0.898	32.207	0.929	34.703	0.945
EDSR* [2]	×4	32	32	32	32.105	0.892	28.540	0.778	27.542	0.731	25.952	0.780	28.890	0.835
Bicubic	×4	32	32	32	28.420	0.810	26.000	0.703	25.960	0.668	23.140	0.658	26.660	0.852
FQSR* (Ours)	×4	4	4	8	31.263	0.880	27.998	0.768	27.218	0.722	25.042	0.752	28.310	0.824
	×4	4	4	32	31.295	0.880	28.015	0.769	27.225	0.722	25.058	0.753	28.304	0.825
	×4	6	6	6	31.956	0.890	28.427	0.777	27.473	0.729	25.718	0.774	28.699	0.832
	×4	6	6	8	32.121	0.892	28.529	0.779	27.542	0.731	25.855	0.779	28.849	0.835
	×4	8	8	8	32.250	0.894	28.632	0.781	27.604	0.733	26.078	0.785	28.979	0.837
	×4	8	8	32	32.275	0.895	28.652	0.782	27.612	0.733	26.124	0.786	29.014	0.838

Table 4: The comparison of our FQSR with full-precision networks on SRGAN with self-ensemble.

Methods	Scale	wt	fm	sc	Set5		Set14		B100		Urban100		DIV2K	
					PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
SRGAN* [1]	×2	32	32	32	37.741	0.958	33.357	0.915	32.033	0.897	31.611	0.923	33.988	0.943
Bicubic	×2	32	32	32	33.660	0.930	30.240	0.869	29.56	0.843	26.880	0.84	31.010	0.939
FQSR* (Ours)	×2	4	4	8	37.46	0.957	32.979	0.911	31.824	0.893	30.698	0.913	33.495	0.938
	×2	4	4	32	37.454	0.957	32.972	0.911	31.792	0.893	30.61	0.912	33.372	0.938
	×2	6	6	6	37.712	0.957	33.302	0.913	32.015	0.895	31.416	0.92	33.994	0.941
	×2	6	6	8	37.809	0.958	33.374	0.915	32.066	0.896	31.554	0.922	34.236	0.942
	×2	8	8	8	37.897	0.959	33.43	0.915	32.106	0.897	31.689	0.923	34.378	0.943
	×2	8	8	32	37.851	0.959	33.351	0.915	32.048	0.896	31.442	0.921	34.229	0.943
SRGAN* [1]	×4	32	32	32	32.079	0.891	28.548	0.778	27.532	0.729	25.936	0.778	28.815	0.834
Bicubic	×4	32	32	32	28.420	0.810	26.000	0.703	25.960	0.668	23.140	0.658	26.66	0.852
FQSR* (Ours)	×4	4	4	8	31.291	0.879	27.998	0.764	27.185	0.717	25.042	0.747	28.109	0.82
	×4	4	4	32	31.56	0.885	28.183	0.77	27.285	0.722	25.248	0.756	28.238	0.824
	×4	6	6	6	32.008	0.89	28.455	0.777	27.488	0.729	25.808	0.775	28.464	0.831
	×4	6	6	8	32.074	0.891	28.5	0.777	27.517	0.728	25.858	0.776	28.791	0.832
	×4	8	8	8	32.163	0.893	28.576	0.779	27.568	0.731	26.003	0.781	28.872	0.835
	×4	8	8	32	32.173	0.893	28.571	0.779	27.562	0.731	25.971	0.78	28.9	0.835