Supplementary Materials of AdderSR: Towards Energy Efficient Image Super-Resolution

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In this document, we supply some details of our proposed AdderSR models. We first provide a brief introduction of energy costs of operations. And then, we further compare the energy cost of 8-bit AdderSR model and its corresponding 8-bit convolutional network. Besides, many super-resolution images of AdderSR models are illustrated in this supplementary material.

1. Energy Costs

It is well known that additions require much lower energy consumptions compared with multiplications. In detail, both Dally [2] and Horowitz [3] reported the energy costs of different operations, which are summarized in Table 1. According to this table, we can compute the energy consumption of whole AdderSR network or convolutional network. Besides models in Table 2 and Table 3 of the main body, we evaluated the performance of AdderSR on NAS-based models including ESRN [4] and FALSR [1]. The proposed method achieves comparable PSNR values (only 0.19dB PSNR drop on average) to those of their baselines with an about $2.5\times$ reduction on the energy consumption.

Although the main advantage for using AdderSR is the reduction on energy consumption, we can obtain an about 16% speed-up using AdderSR on FPGA (Xilinx XC7Z010 chip) under the same architecture [6].

We further quantize the models using both convolution and adder filters to 8-bit values, the results of 8-bit super-resolution networks on four benchmark databases are reported in Table 3. It shows that the average PSNR gap between 8-bit AdderSR models and 8-bit convolutional network over all datasets is still less than 0.2dB. Then, we can obtain an about $3.8\times$ reduction on the energy consumption using the proposed AdderSR with comparable performance. The energy consumptions of 8-bit AdderSR network and 8-bit convolutional network are summarized in Table 2. This significant reduction on energy consumption will make these deep learning models portable on the mobile devices.

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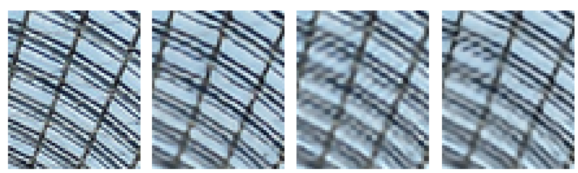
Table 1. The energy costs of different operations. The results are reported in literatures [2, 3, 5].

Operation	8 bit	32 bit	16 FP	32 FP
Addition (*pJ*)	0.03	0.1	0.4	0.9
Multiplication (*pJ*)	0.2	3.1	1.1	3.7

Table 2. The energy consumptions of different networks with 8-bit values on $\times 2$ scale. The energy cost is computed using 720p (*i.e.* 1280×720) high-resolution image.

Model	VDSR		EDSR	
	CNN	ANN	CNN	ANN
Energy cost (*pJ*)	140.9G	**36.9G**	2127.2G	**556.3G**



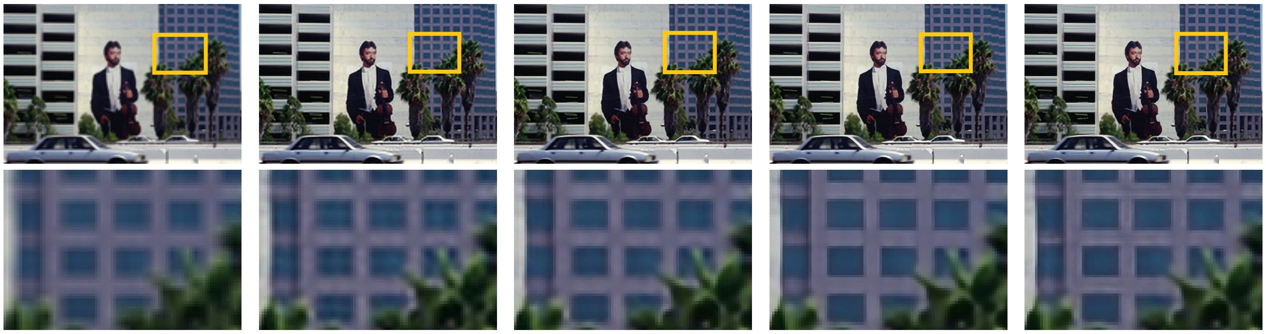
Ground-truth (PSNR, SSIM) | **Adder-CARN (20.57, 0.8767)** | Pruned-CARN (17.70, 0.6760) | Quantized-CARN (18.55, 0.7468)

Figure 1. Visualization of outputs generated by different models.

2. Visualizations

Both quantitative comparison and visual quality comparison of the same network architecture using both additions and multiplications are conducted in the "experiments" section. Here, we provide more visual comparison results of benchmark datasets in Fig. 3. Actually, since the PSNR values of AdderSR and its baselines are much closed, the output high-resolution images are of the similar visual quality.

In subsection "ablation study" of main body, we conducted experiments to evaluate the functionality of two proposed novel operations. The quantitative comparison is analyzed in the main body. Here, we further offer more visualization results to show their functionality. The experimental results are illustrated in Fig. 2. It shows that the output images of AdderSR network with self-shortcut operation preserve more details information than those of the model without self-shortcut operation. In addition, high-frequency in-



Input Image Bicubic PSNR: 25.85 | Self-shortcut: × Power act. : × PSNR: 27.35 | Self-shortcut: ✓ Power act. : × PSNR: 28.55 | Self-shortcut: ✓ Power act. : ✓ PSNR: 28.88 | Convolution VDSR PSNR: 29.04

Figure 2. Visualization of super-resolution image of different AdderSR Networks and convolutional VDSR on $\times$ 3 scale (image is from B100 dataset).

Table 3. Quantitative results of 8-bit convolutional networks and 8-bit AdderSR models. Wherein, $\times 2$, is the output scaling factor for the SISR task. ANN and CNN denote the networks using adder units and traditional convolution layers, respectively.

Scale	Model	Type	#Mul. (G)	#Add. (G)	Set5 PSNR	Set14 PSNR	B100 PSNR	Urban100 PSNR
$\times 2$	VDSR	ANN	1.1	1224.1	37.15	32.85	31.66	30.17
		CNN	612.6	612.6	37.29	32.95	31.75	30.48
	EDSR	ANN	7.9	18489.8	37.84	33.60	32.19	32.18
		CNN	9248.9	9248.9	38.02	33.79	32.27	32.56

formation (e.g., edge, corner) is emphasized with the help of power activation function. In summary, by exploiting the proposed method, we can generate features with abundant texture and establish effective SISR models using only additions.

The energy-quality comparisons to pruned CARN is shown in Fig. 1 and Table 3 from the main body. The performance of 8bit quantized CNN and AdderNet models are reported in Table 2 and Table 3. In summary, our approach can be well embedded into low-energy CNN models. For example, the Adder-CARN model achieves 0.4dB PSNR higher than the pruned CARN-$\frac{2}{3}$ while consumes very close energy cost (402G pJ *vs*. 404G pJ). Regarding visual quality, output images of AdderSR and other energy-saving methods with close energy consumption are compared in Fig. 1. AdderSR reconstructs better texture.

References

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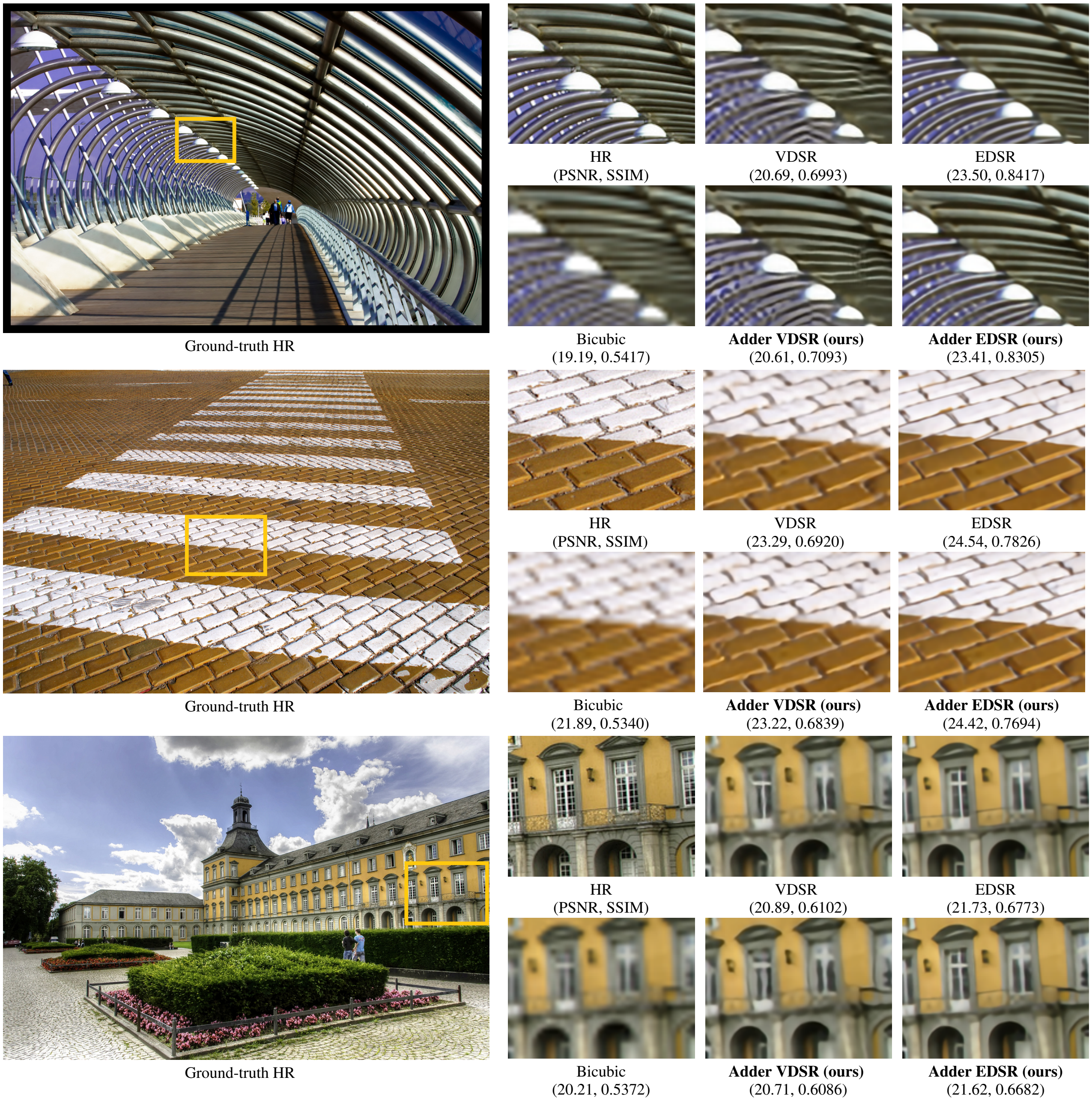

Figure 3. Visualization of super-resolution image of AdderSR Network and CNN on $\times 4$ scale (Urban100 database).