SF-CNN: A Fast Compression Artifacts Removal via Spatial-to-Frequency Convolutional Neural Networks

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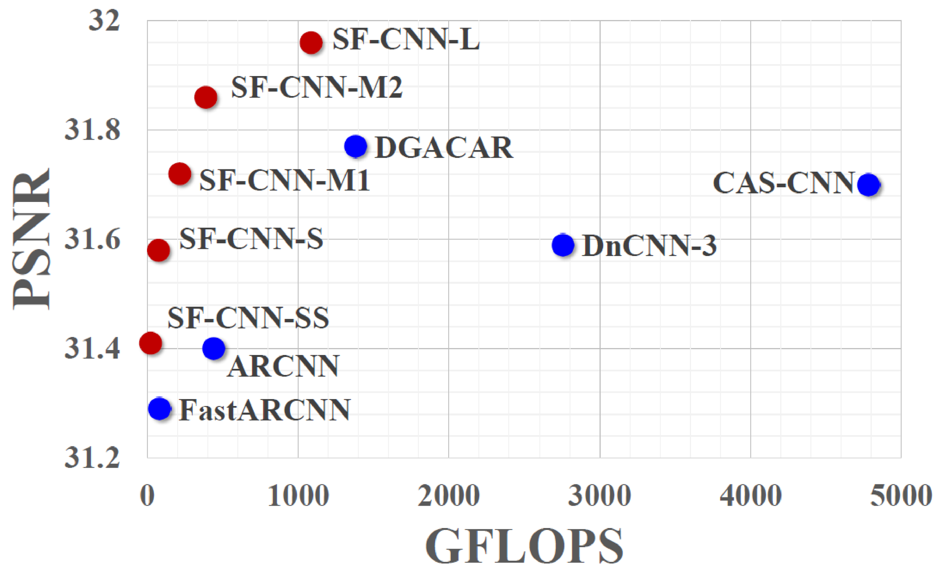
Abstract

- We Propose Efficient CNNs for Image Restoration, Especially for DeJPEG
- Computational Complexity of Most of the CNN-based Image Restoration Networks is $H \times W \times C_{in} \times C_{out} \times K_H \times K_W \times L$
- Our Goal is to Reduce $H \times W$ via Spatial Downsampling

Related Works

CNNs for Compression Artifacts Removal

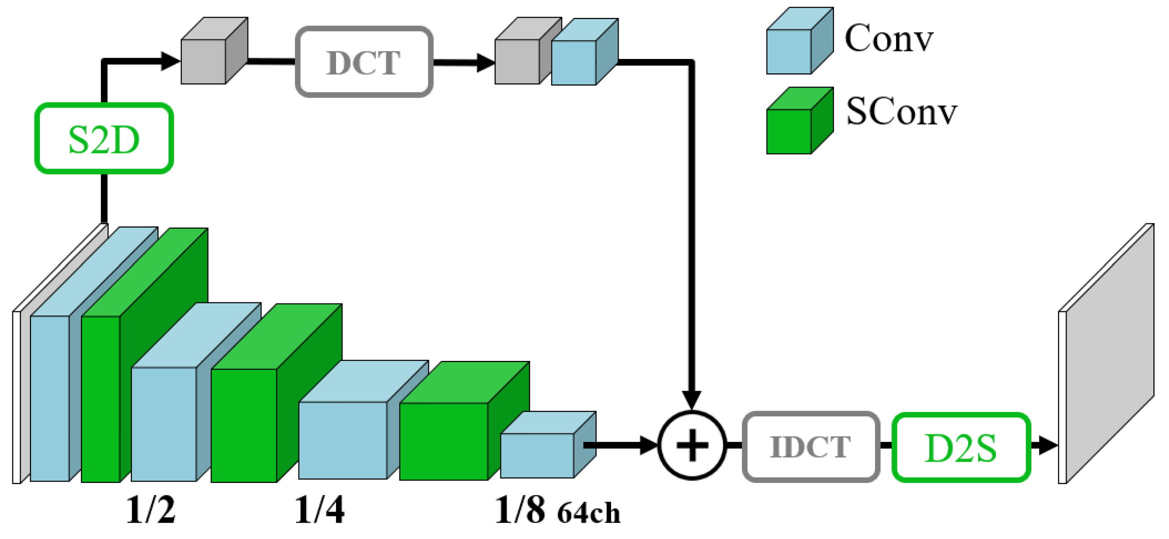
- *Full-Resolution, Shallow Network [1]*
- *Full-Resolution, Better Performance [3, 6, 8]*
- *Downsampling by 2 [2, 5]*
- *Encoder-Decoder Shape and Skip-Connections [4, 7]*

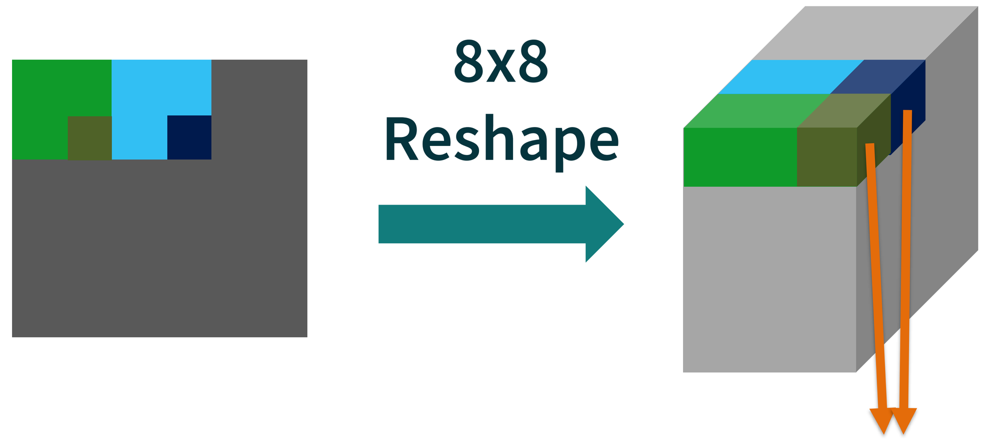


PSNR-Complexity Plot on LIVE1 QF=20, Full-HD Resolution

SF-CNN

- Reshaping from Spatial to a Channel Can Reduce Spatial Dimension in Networks. Our Network Predicts Reshaped Desired Output from the Input.
- However, to Reshape in the Spatial Domain Does Not Fit in Convolutional Filters (S2S)
- The Network with the Reshaped Input is too Small to Learn Convolutional Repersentations (F2F)
- Spatial-to-Frequency Network is More Suitable (S2F)
- We Used 1x1 Convolution without Gradient for Block-wise DCT and IDCT Layers as in [8]





Two Pixels are Not Correlated in the Spatial Domain but Correlated in the Frequecny Domain

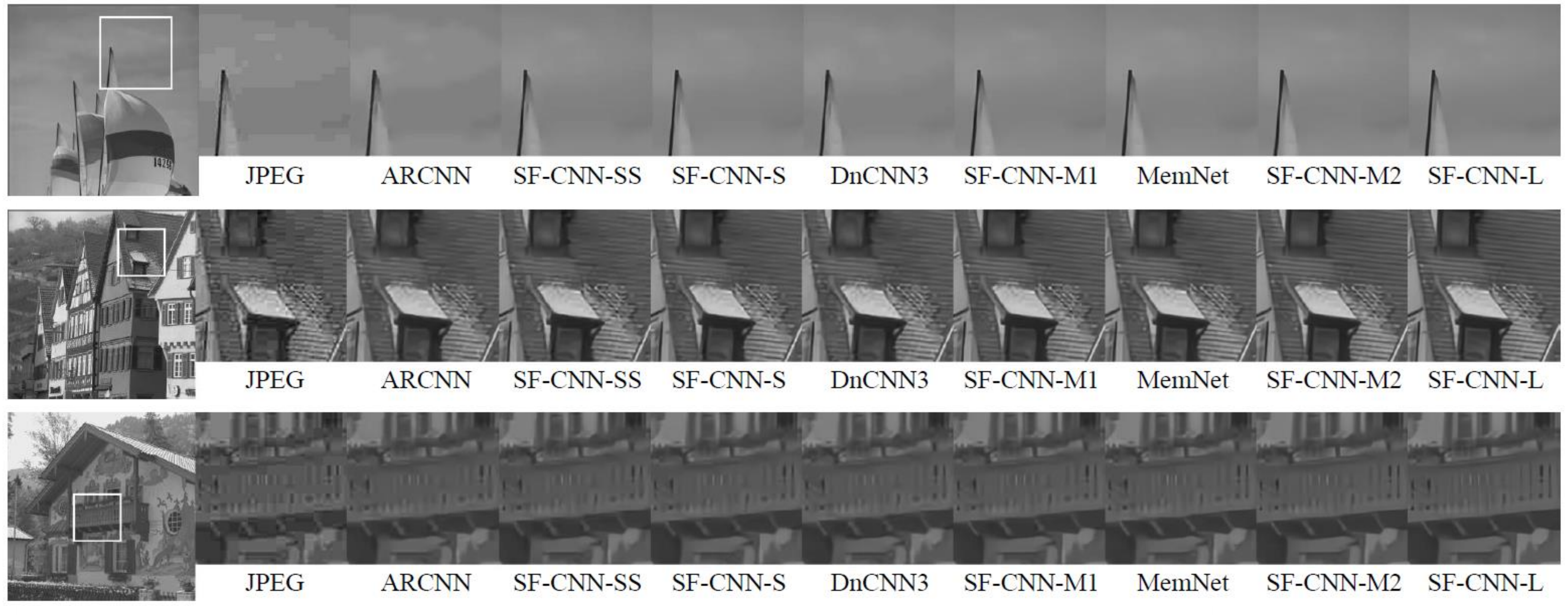
Network	F2F	S2S	S2F(Ours)
PSNR	31.59	31.67	**31.72**

Ablation Study between Two Domains

Results

	QF10			QF20			
	GFLOPs	PSNR	SSIM	PSNR-B	PSNR	SSIM	PSNR-B
JPEG	-	27.77	0.791	25.33	30.07	0.868	27.57
Fast-ARCNN	83.1	29.10	0.824	28.65	31.29	0.887	30.54
ARCNN	441.5	29.13	0.823	28.74	31.40	0.889	30.69
SF-CNN-SS	**20.8**	**29.14**	**0.826**	28.58	**31.41**	**0.890**	30.55
SF-CNN-S	**73.9**	**29.28**	**0.829**	**28.81**	**31.58**	**0.894**	**30.85**
DnCNN-3	2756.7	29.19	0.826	28.90	31.59	0.894	**31.07**
CAS-CNN	4784.8	**29.44**	**0.833**	**29.19**	31.70	0.895	30.88
SF-CNN-M1	**214.2**	29.40	0.831	28.95	**31.72**	**0.896**	31.03
DGACAR	1380.7	29.45	0.834	29.10	31.77	0.896	31.26
MemNet	7920.7	29.47	0.834	29.04	31.83	0.897	31.14
SF-CNN-M2	**387.2**	**29.54**	**0.835**	**29.11**	**31.86**	**0.898**	**31.23**
SF-CNN-L	**1084.8**	**29.61**	**0.838**	**29.20**	**31.96**	**0.900**	**31.34**

PSNR/FLOPs on LIVE1 Dataset



Qualitative Results on sailing2, paintedhouse and buildings (QF=10)

References

[1] Chao Dong et al, ARCNN, CVPR 2015

[2] Ke Yu et al, Fast-ARCNN, Arxiv 2016

[3] Kai Zhang et al, DnCNN, IEEE TIP 2017

[4] Lukas Cavigelli et al, CAS-CNN, IJCNN 2017

[5] Leonardo Galteri et al, DGACAR (ARGAN), ICCV 2017

[6] Ying Tai et al, MemNet, CVPR 2017

[7] X. Zhang et al, DMCNN, ICIP 2018

[8] Jun Guo and Hongyang Chao, DDCN, ECCV 2016