Development of New Fractal and Non-fractal Deep Residual Networks for Deblocking of JPEG Decompressed Images

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- JPEG Image Compression

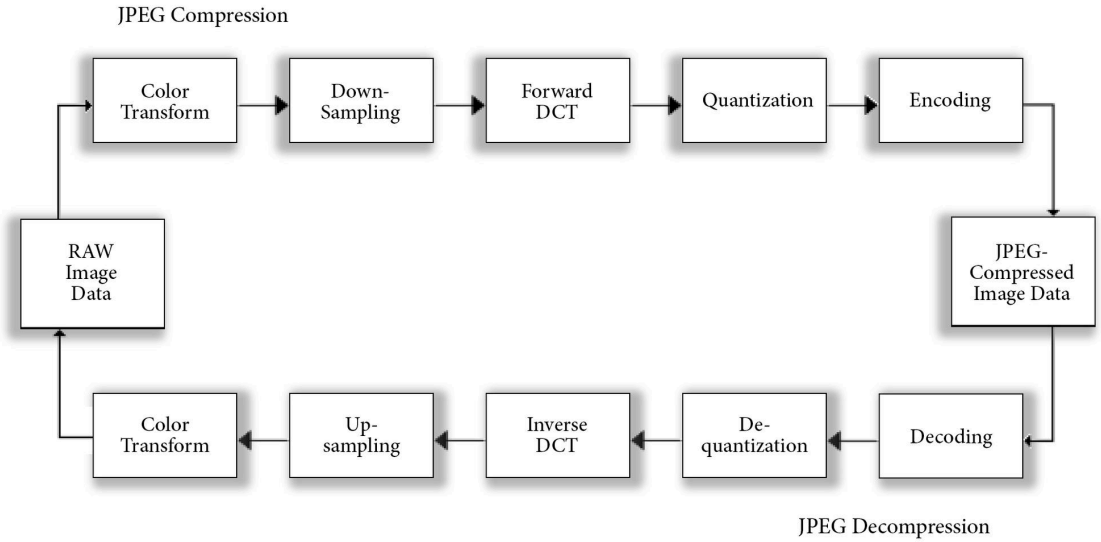


Fig. 1. JPEG Image Compression and Decompression (Ref. https://beyondresolution.info/JPEG-THE-GUY-BEHIND-THE-GUY-BEHIND-THE-GUY)

- The scheme is applied to the image blocks of size 8×8.

Deep JPEG Image Deblocking Networks

- ARCNN → Shallow Network

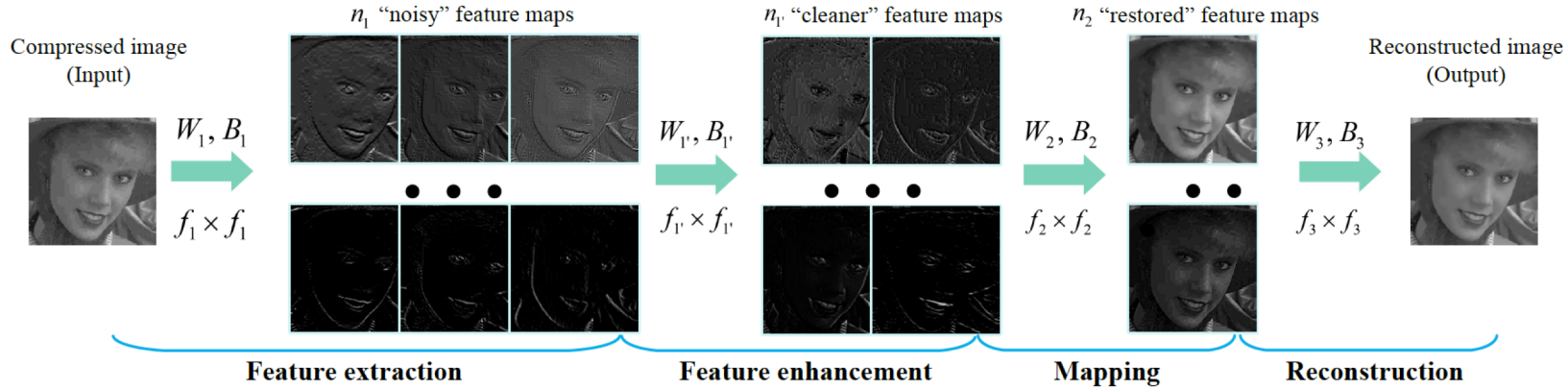


Fig. 2. Architecture of ARCNN. (Ref.: [1])

- DCSC → Sparse Representation Convolutional Neural Networks

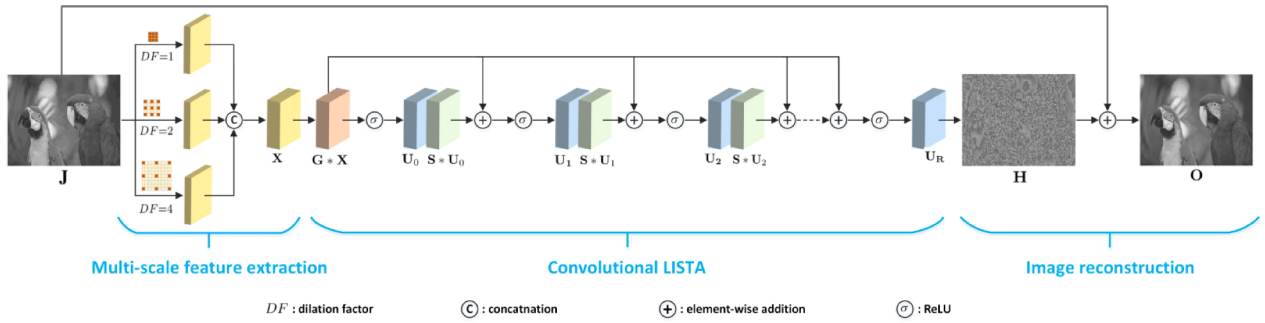


Fig. 3. Architecture of DCSC. (Ref.: [2])

Deep JPEG Image Deblocking Networks

- DnCNN → Residual Learning, Convolution+BN+ReLU

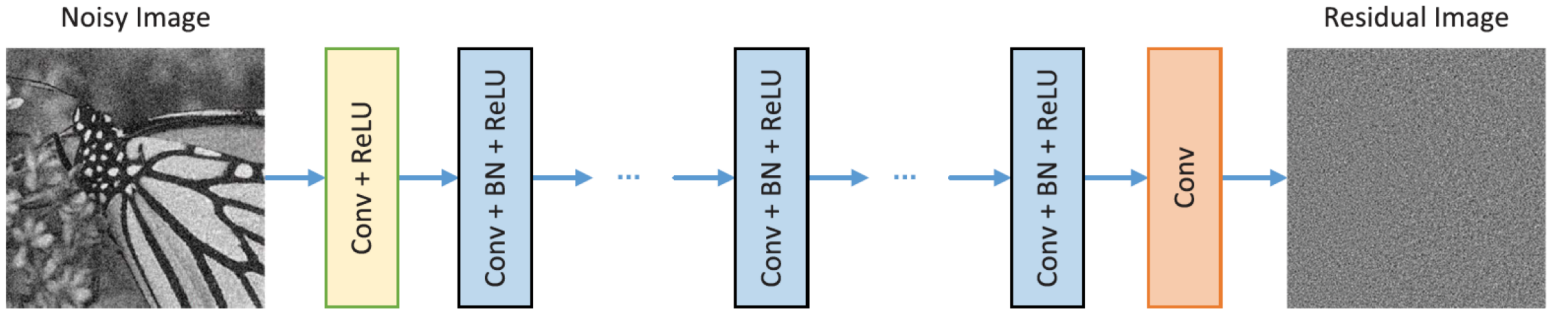


Fig. 4. Architecture of DnCNN. (Ref.: [3])

- DRMU → Residual Maxout Units

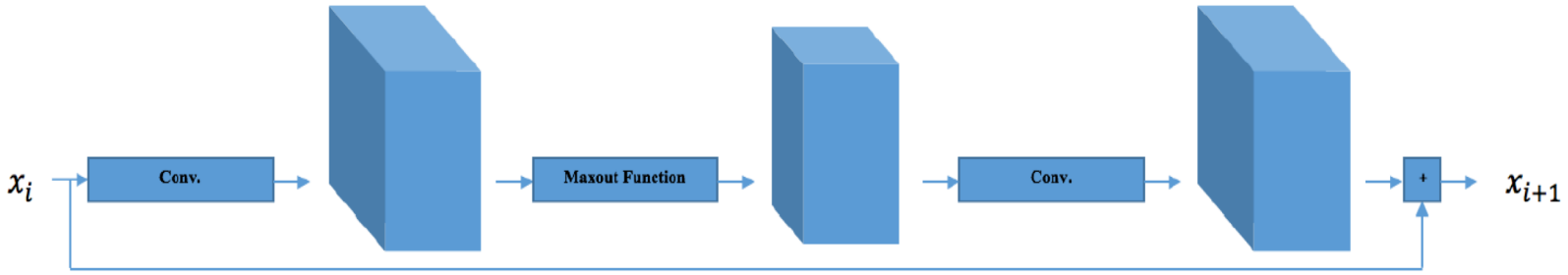
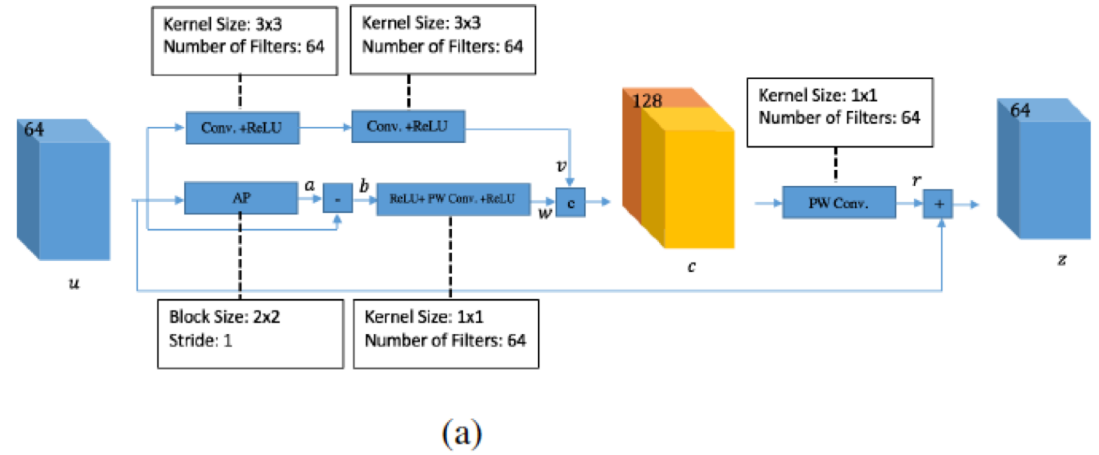


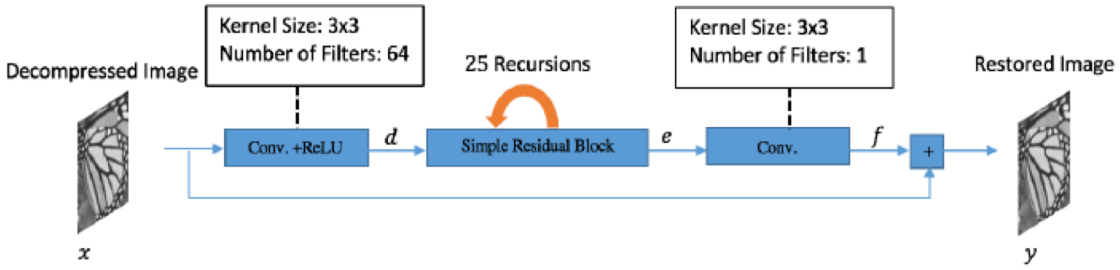
Fig. 5. Architecture of DRMU. (Ref.: [4])

Proposed Recursive Deblocking Network

- Simple Residual Block → Hierarchical Residual Features
  → High Frequency Residual Features



(a)



(b)

Fig. 6. Architecture of the Proposed Recursive Network.
(a) Simple Residual Block (SRB).
(b) Recursive Deblocking Network.

Proposed Fractal Deblocking Network

- Compound Residual Block

Replacing each convolution in SRB by SRB itself

Fusing features from various levels of abstraction

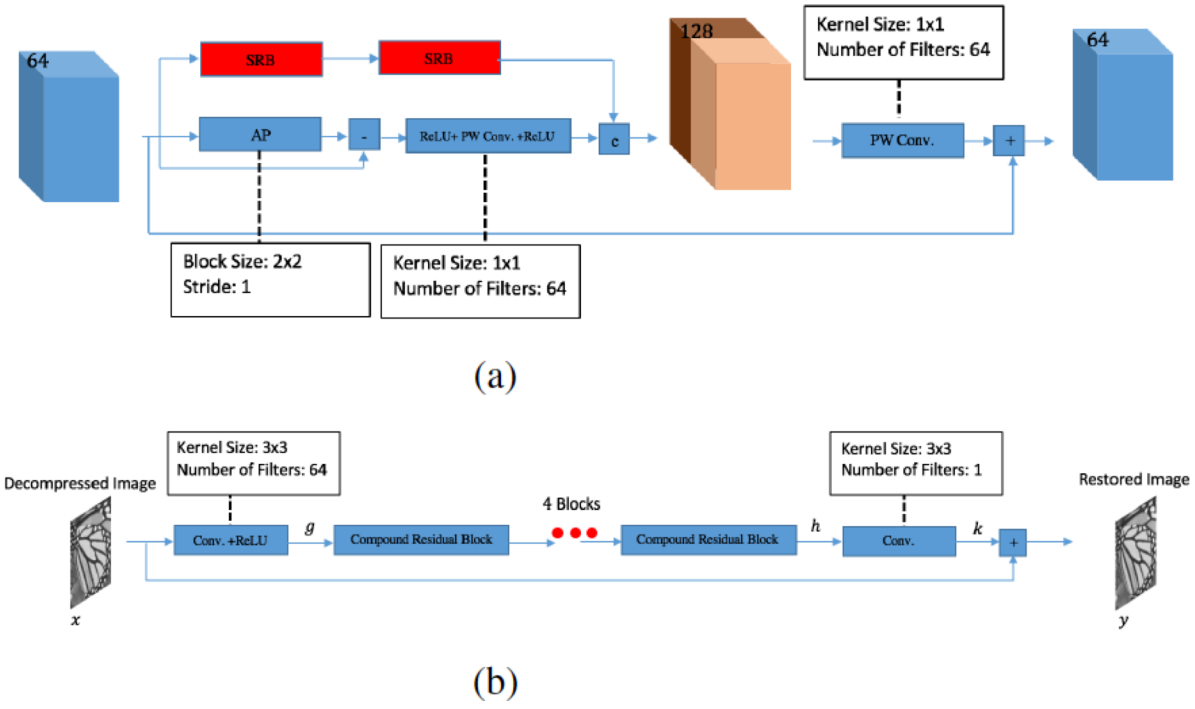


Fig. 7. Architecture of the Proposed Fractal Network.
(a) Compound Residual Block (CRB).
(b) Fractal Deblocking Network.

Ablation Studies

Networks

- RN: Recursive Network with SRB
- RN with SRB Variant: Recursive Network employing SRB without High Frequency Residual Feature Generation Branch
- NN: Non-recursive Fractal Network with CRB
- NN with SRB: Non-recursive Network with SRB

Table 1. Ablation Studies.

Dataset	RN with *SRB Variant*	RN	NN with *SRB*	NN
Classic5	29.21 (0.7993)	29.28 (0.8010)	29.46 (0.8053)	29.56 (0.8088)
Live1	29.20 (0.8149)	29.23 (0.8157)	29.33 (0.8183)	29.42 (0.8208)

Network Performance

- Impact of number of recursions on the performance of the recursive network.

Table 2. Performance vs Number of Recursions

Dataset	5 Recursions	15 Recursions	25 Recursions
Classic5	28.89 (0.7880)	29.01 (0.7920)	29.28 (0.8010)
Live1	28.93 (0.8056)	29.04 (0.8091)	29.23 (0.8157)

- Comparison between the performance and complexity of the various deep JPEG image deblocking networks.

Table 3. Performance and Number of Parameters of Various Schemes

Dataset	Quality Factor	JPEG	ARCNN	TNRD	DCSC	Proposed	DnCNN	LPIO	DRMU	Proposed
Classic5	10	27.82 (0.7595)	29.03 (0.7929)	29.28 (0.7992)	29.25 (0.8030)	29.28 (0.8010)	29.40 (0.8030)	29.35 (0.8010)	29.43 (0.8041)	29.56 (0.8088)
	20	30.12 (0.8344)	31.15 (0.8517)	31.47 (0.8576)	31.43 (0.8600)	31.41(0.8578)	31.63 (0.8610)	31.58 (0.8560)	31.63 (0.8613)	31.78(0.8642)
Live1 [15]	10	27.77 (0.7730)	28.96 (0.8076)	29.15 (0.8111)	29.17 (0.8150)	29.23 (0.8157)	29.19 (0.8120)	29.17 (0.8110)	29.31 (0.8178)	29.42 (0.8208)
	20	30.07 (0.8512)	31.29 (0.8733)	31.46 (0.8769)	31.48 (0.8800)	31.51 (0.8803)	31.59 (0.8800)	31.52 (0.8760)	31.67 (0.8832)	31.80(0.8857)
Number of Parameters		-	106K	21K	94K	91K	737K	1394K	761K	728K

Visual Quality of the Deblocked Images

- Visual quality of the deblocked *lighthouse* images obtained by the proposed networks, when quality factor is 10.

Fig. 8. Visual qualities. (a) GT. (b) JPEG Image. (c) Recursive Network. (d) Fractal Network.

Conclusion

- Two deep light-weight deblocking networks have been proposed.
- The proposed residual block uses two feature generation strategies for image deblocking, namely, hierarchical residual feature generation and high frequency residual feature generation.
- The two types of features generated by the proposed residual block have been fused in order to increase the representational capability of the network.
- Both of the proposed deblocking networks have outperformed the state-of-the-art deblocking schemes in terms of network performance and complexity.

References

[1] C. Dong, Y. Deng, C.C. Loy and X. Tang, ”Compression artifacts reduction by a deep convolutional network”, In ICCV , 2015.

[2] X. Fu, Z-J Zha, F. Wu, X. Ding and J. Paisley, ”JPEG artifact reduction via deep convolutional sparse coding, In ICCV , 2019.

[3] K. Zhang,W. Zuo, Y. Chen, D. Meng, and L. Zhang, ”Beyond a gaussian denoiser: residual learning of deep CNN for image denoising”, IEEE Transactions on Image Processing, 2017.

[4] A. Esmaeilzehi, M. O. Ahmad and M.N.S. Swamy, ”Deep JPEG image deblocking using residual maxout units”, In ICIP , 2019.

Thank You

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