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Lightweight Image Super-Resolution Reconstruction With Hierarchical Feature-driven Network

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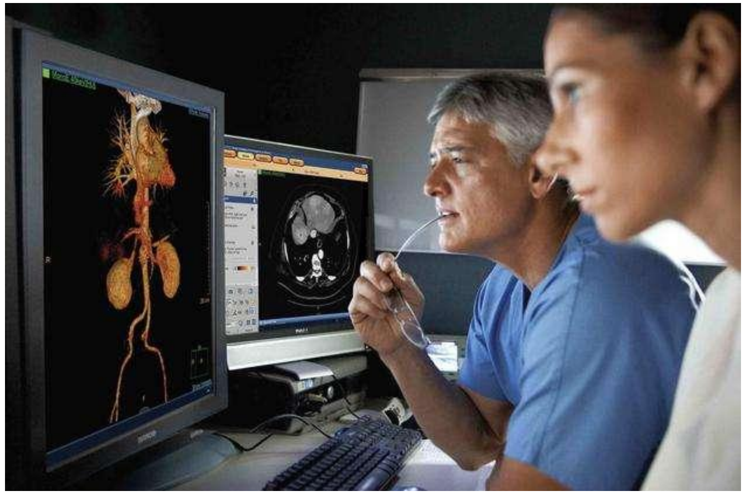
Background

- **Wide application of high-quality images.**

HD movies

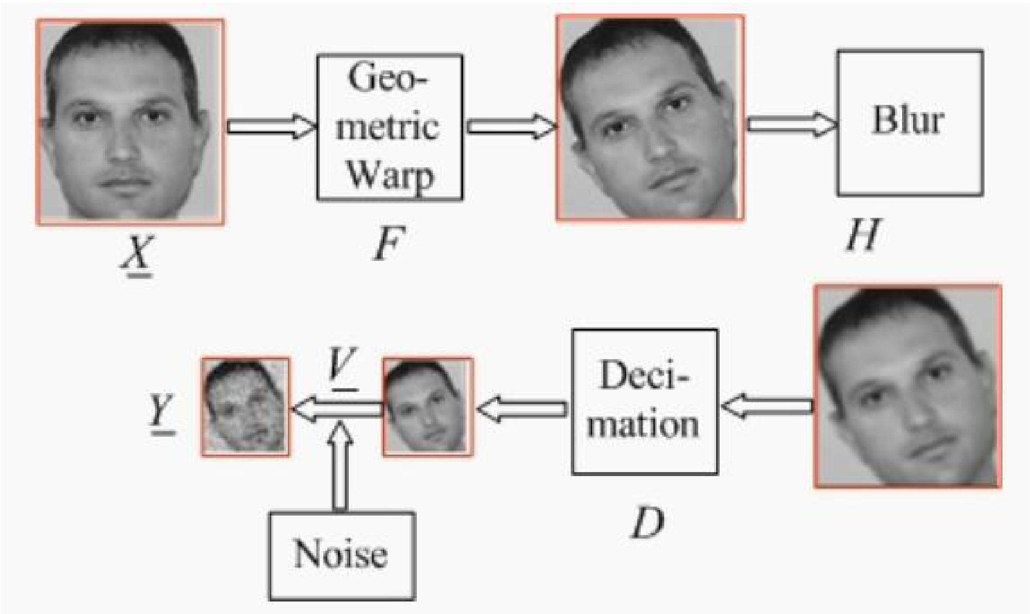


Medical imaging

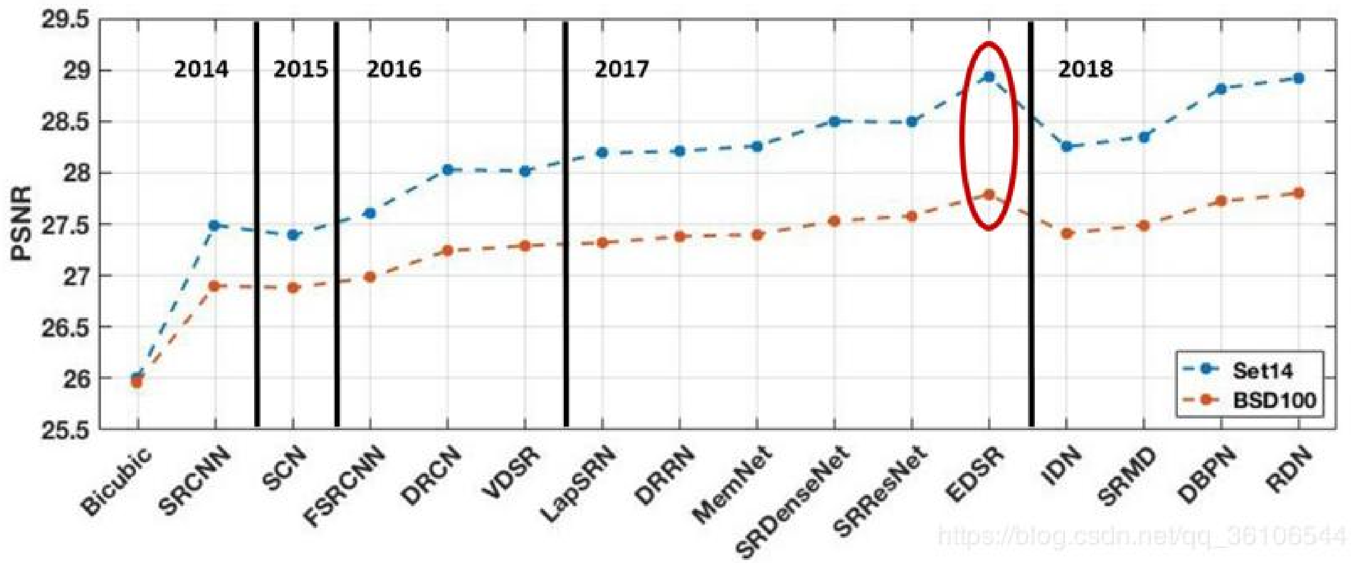
Public security

Background

- **Problem**

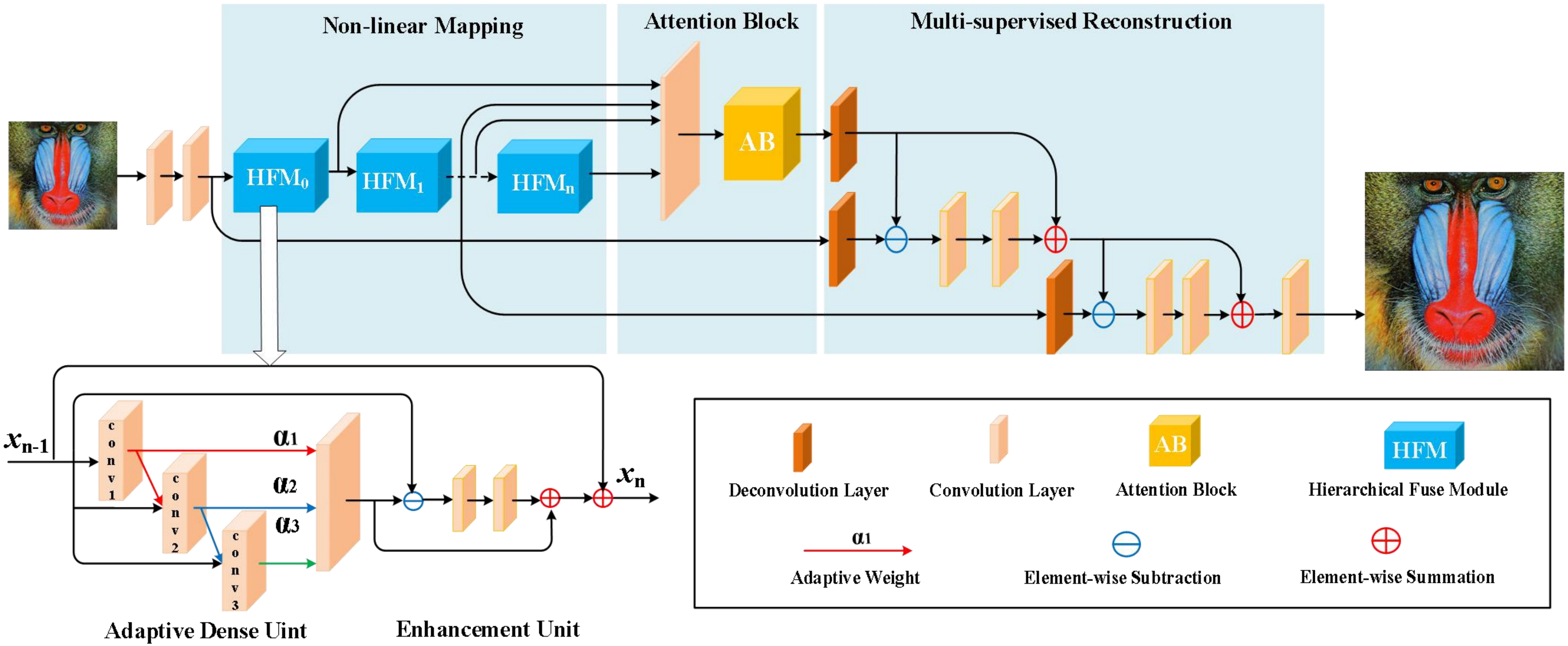


Imaging process



Increased network depth leads to increased parameters

Method

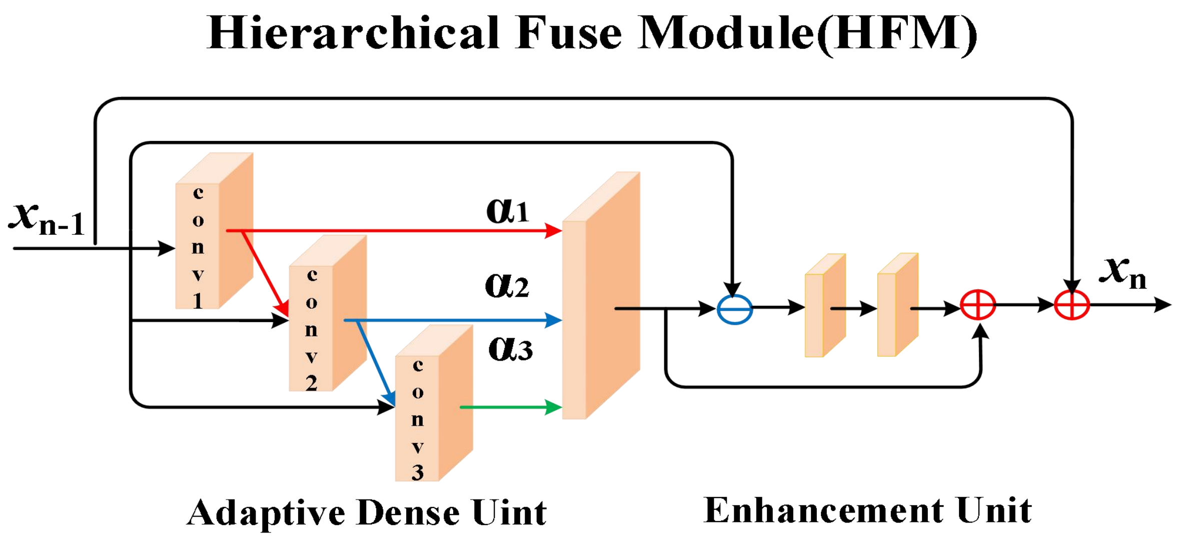


The complete architecture of our proposed model.

- The proposed network contains four parts: shallow feature extraction, non-linear mapping, attention block and multi-supervised reconstruction.

Method

- Non-linear Mapping

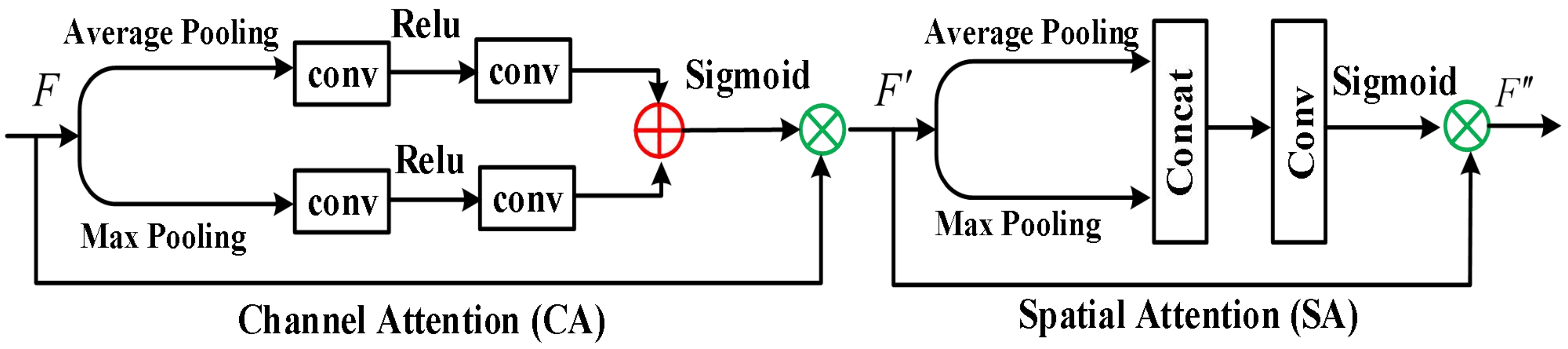


The structure of hierarchical fuse module (HFM).

- The non-linear mapping module is stacked with several hierarchical fuse module (HFM), the HFM contains an adaptive dense unit (ADU) and an enhancement unit (EU).
- The ADU can make full use of local hierarchical features to achieve feature reuse.
- The EU in HFM is used to further refine feature information extracted from ADU.

Method

- Attention Block

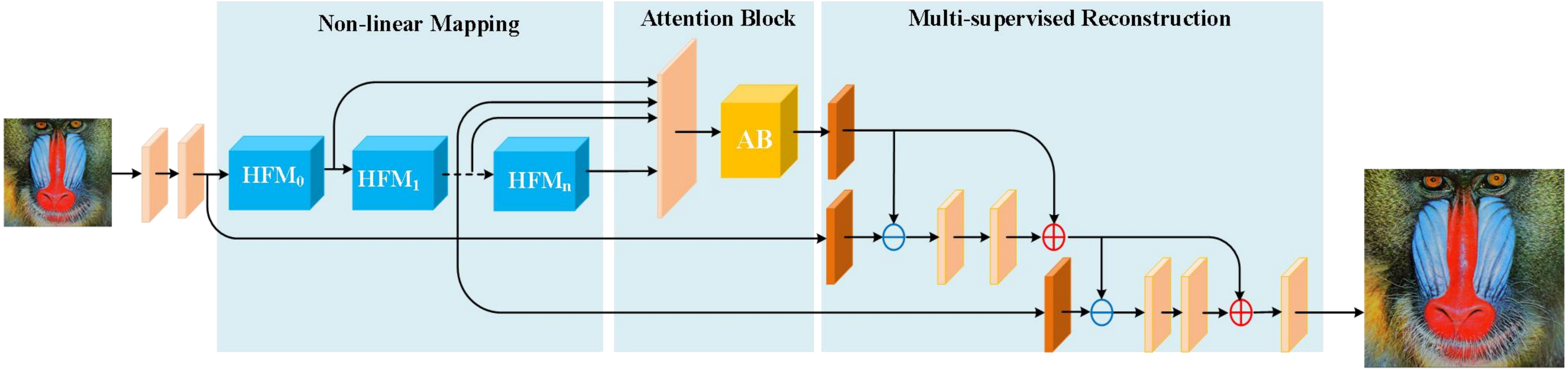


The structure of attention block (AB).

- We introduce both channel and spatial attention to make our network focus on important features and suppress unnecessary ones.

Method

- Multi-supervised Reconstruction



- In the image reconstruction part, we introduce three deconvolution layers to reconstruct three intermediate SR images from shallow, middle and deep levels of network, and gradually combine them to obtain the final high-quality image.

Experiment

- Evaluation Criteria

- Evaluation index: PSNR,SSIM, Network parameters, Multiply-accumulate operations

- Comparison algorithm: VDSR[1], DRRN[2], MemNet[3], MoreMNAS-A[4], IDN[5], TSCN[6], LCSC-76-291[7], AWSRN-S[8]

- Deep learning framework: Pytorch

- Learning rate: begins with 0.0001 and stops at 0.00001

- Input: For scale factor 2, 3 and 4, the sizes of the LR patches are 48, 32, and 24, respectively

- Optimizer: Adam

- Loss: The combination of L1 loss and structural similarity loss

[1] J. Kim, J. K. Lee, and K. M. Lee, "Accurate image super-resolution using very deep convolutional networks," in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 1646-1654, 2016.
[2] Y. Tai, J. Yang, and X. Liu, "Image super-resolution via deep recursive residual network," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 3147-3155, 2017.
[3] Y. Tai, J. Yang, X. M. Liu, and C. Y. Xu, "MemNet: A Persistent Memory Network for Image Restoration," in IEEE International Conference on Computer Vision (ICCV), pp. 4539-4547, 2017.
[4] X. Chu, B. Zhang, R. Xu, and H. Ma, "Multi-objective reinforced evolution in mobile neural architecture search," in arXiv preprint arXiv:1901.01074, 2019.
[5] Z. Hui, X. M. Wang, and X. B. Gao, "Fast and accurate single image super-resolution via information distillation network," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 723-731, 2018.
[6] Z. Hui, X. M. Wang, and X. B. Gao, "Two-stage convolutional network for image super-resolution," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 2670-2675, 2018.
[7] W. M. Yang, X. C. Zhang, Y. P. Tian, W. Wang, J. H. Xue and Q. M. Liao, "LCSCNet: Linear compressing-based skip-connecting network for image super-resolution," in IEEE Transactions on Image Processing, pp. 1450-1464, 2019.
[8] C. F. Wang, Z. Li and J. Shi, "Lightweight image super-resolution with adaptive weighted learning network," in arXiv preprint arXiv:1904.02358, 2019.

Experiment

- Qualitative results

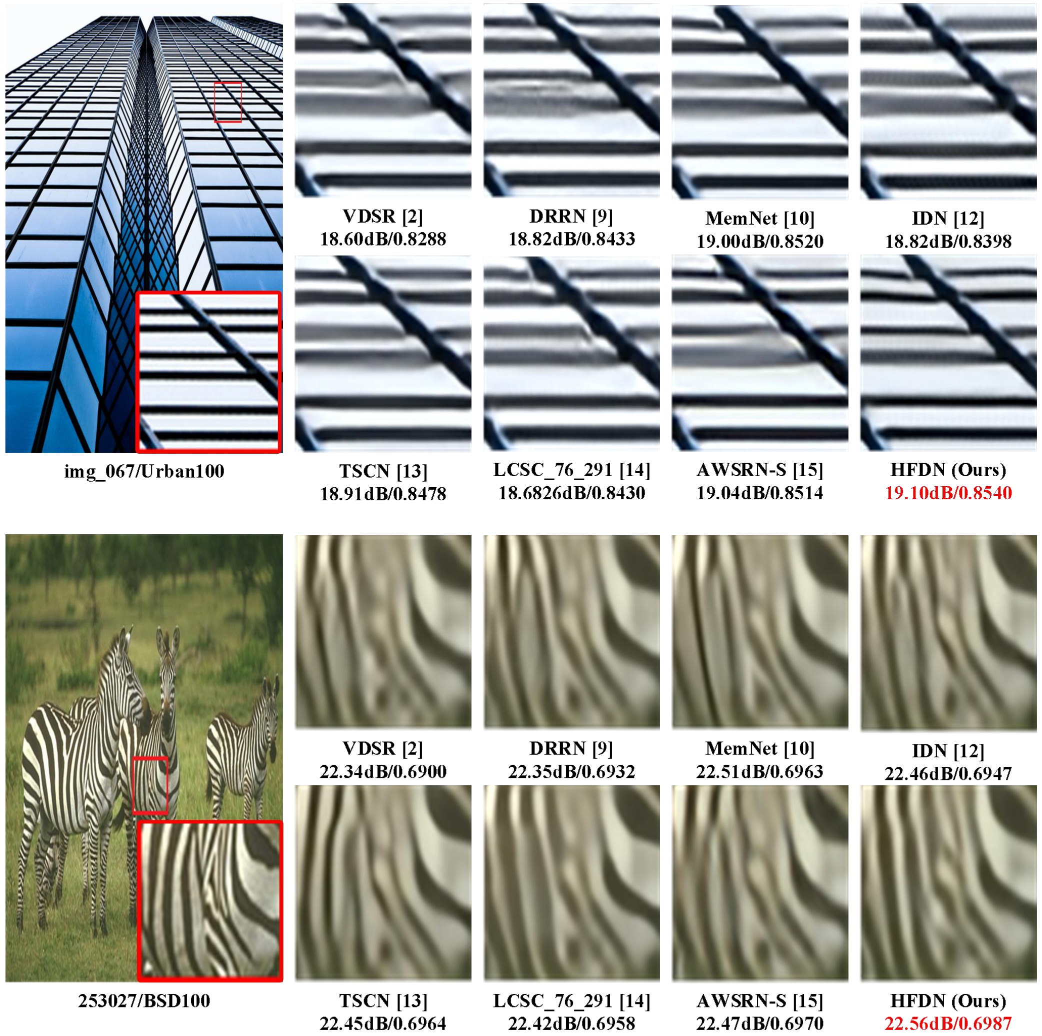
Qualitative results on benchmark datasets.

Scale	Algorithms	Para/MACC	Set5 PSNR/SSIM	Set14 PSNR/SSIM	BSD100 PSNR/SSIM	Urban100 PSNR/SSIM
×2	VDSR [2]	665k/612.6G	37.53/0.9587	33.03/0.9124	31.90/0.8960	30.76/0.9140
	DRRN [9]	297k/6796.9G	37.74/0.9591	33.23/0.9136	32.05/0.8973	31.23/0.9188
	MemNet [10]	677k/2662.4G	37.78/0.9597	33.28/0.9142	32.08/0.8978	31.31/0.9195
	MoreMNAS-A [11]	1039k/238.6G	37.63/0.9584	33.23/0.9138	31.95/0.8961	31.24/0.9187
	IDN [12]	553k/202.8G	37.83/0.9600	33.30/0.9148	32.08/0.8985	31.27/0.9196
	TSCN [13]	784.77k/225.7G	37.88/0.9602	33.28/0.9147	32.09/0.8985	31.29/0.9198
	LCSC_76_291 [14]	1844k/1024.1G	37.86/0.9600	33.34/0.9146	32.10/0.8985	31.34/0.9204
	AWSRN-S [15]	397k/91.2G	37.75/0.9596	33.31/0.9151	32.00/0.8974	31.39/0.9207
	HFDN	760.1k/260.7G	37.95/0.9603	33.46/0.9162	32.11/0.9031	31.52/0.9252
	HFDN+	760.1k/260.7G	38.05/0.9607	33.59/0.9168	32.16/0.9035	31.72/0.9268
×3	VDSR [2]	665k/612.6G	33.66/0.9213	29.77/0.8314	28.82/0.7976	27.14/0.8279
	DRRN [9]	297k/6796.9G	34.03/0.9244	29.96/0.8349	28.95/0.8004	27.53/0.8378
	MemNet [10]	677k/2662.4G	34.09/0.9248	30.00/0.8350	28.96/0.8001	27.56/0.8376
	IDN [12]	553k/30.8G	34.11/0.9253	29.99/0.8354	28.95/0.8013	27.42/0.8359
	TSCN [13]	821.63k/157.99	34.18/0.9256	29.99/0.8351	28.95/0.8012	27.46/0.8362
	LCSC_76_291 [14]	1844k/797.6G	34.13/0.9254	29.95/0.8348	28.97/0.8014	27.53/0.8377
	AWSRN-S [15]	477k/48.6G	34.04/0.9240	30.09/0.8376	28.92/0.8009	27.57/0.8391
	HFDN	823k/248.21G	34.21/0.9256	30.05/0.8395	28.93/0.8077	27.51/0.8471
	HFDN+	823k/248.21G	34.29/0.9263	30.17/0.8402	29.00/0.8085	27.72/0.8497
×4	VDSR [2]	665k/612.6G	31.35/0.8838	28.02/0.7674	27.29/0.7251	25.18/0.7524
	DRRN [9]	297k/6796.9G	31.68/0.8888	28.21/0.7721	27.38/0.7284	25.44/0.7638
	MemNet [10]	677k/2662.4G	31.74//0.8893	28.26/0.7723	27.40/0.7281	25.50/0.7630
	IDN [12]	553k/89G	31.82/0.8903	28.25/0.7730	27.41/0.7297	25.41/0.7632
	TSCN [13]	981.38/139.55	31.82/0.8907	28.28/0.7734	27.42/0.7301	25.44/0.7644
	LCSC_76_291 [14]	1844k/726.3G	31.76/0.8899	28.20/0.7731	27.36/0.7293	25.38/0.7643
	AWSRN-S [15]	588k/33.7G	31.77/0.8893	28.35/0.7761	27.41/0.7304	25.56/0.7678
	HFDN	760.1k/178.51G	31.86/0.8920	28.26/0.7778	27.42/0.7367	25.54/0.7700
	HFDN+	760.1k/178.51G	31.95/0.8935	28.37/0.7800	27.44/0.7373	25.69/0.7736

- The proposed HFDN+ performs the best on all scale factors and all datasets. Even without self-ensemble, our algorithm achieves best results in most cases.

Experiment

- Visual results



Visual comparison of the ×4 super-resolution results of our HFDN and the state-of-the-art algorithms.

Experiment

- The effect of attention block (AB)

Results of ablation study on effects of different attention blocks. The experiments are conducted on Set5 dataset with scale ×3.

Methods	Baseline	CA	SA	CA&SA
PSNR(dB)	34.16	34.19	34.17	**34.21**

- Only using channel attention (CA) or spatial attention (SA) can slightly improve the results.
- When CA and SA are integrated into the network simultaneously, the PSNR is significantly improved.

Experiment

- The effect of ADU

Investigation of ADU. The experiments are conducted on scale ×4.

	ADU/NA	Dense	ADU
Set14	28.02	27.98	**28.26**
Urban100	25.53	25.49	**25.54**

- ADU/NA indicates the network that without adaptive weights when performing channel-wise concatenation.
- “Dense” in the table means dense block.

Experiment

- The effect of multi-supervised reconstruction strategy.

Investigation of MSR. The experiments are conducted on scale ×4.

	d-level	s&d-levels	s&d&m-levels
Set14	27.87	28.00	**28.26**
Urban100	25.48	25.52	**25.54**

- We train three networks with one deconvolution layer in the deep level, represented as (d-level), two deconvolution layers in both shallow and deep levels (s&d levels), and three deconvolution layers in the shallow, deep and middle levels (s&d&m-levels) of network respectively.

Conclusions

- **Conclusions**

- We present a lightweight hierarchical feature-driven network for single image super-resolution.
- We construct a novel hierarchical fuse module to effectively reuse local hierarchical information and adaptively combine the valuable features.
- We introduce the channel and spatial attention to improve the discriminative learning ability of network.
- We explore a multi-supervised reconstruction method to utilize global hierarchical information in network.
- The experimental results demonstrate that our proposed method obtains a superior performance.
- In future work, we intend to study better optimization strategies.

Thank You!

For any question, please contact:
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