Single Image Super-Resolution via Global-Context Attention Networks

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1. Introduction

In the last few years, single image super-resolution (SISR) has benefited a lot from the rapid development of deep convolutional neural networks (CNNs), and the introduction of attention mechanisms further improves the performance of SISR. However, previous methods use one or more types of attention independently in multiple stages and ignore the correlations between different layers in the network. To address these issues, we propose a novel end-to-end architecture named global-context attention network (GCAN) for SISR, which consists of several residual global-context attention blocks (RGCABs) and an inter-group fusion module (IGFM). Specifically, the proposed RGCAB extracts representative features that capture non-local spatial interdependencies and multiple channel relations. Then the IGFM aggregates and fuses hierarchical features of multi-layers discriminatively by considering correlations among layers. Extensive experimental results demonstrate that our method achieves superior results against other state-of-the-art methods on publicly available datasets.

2. Network Architecture

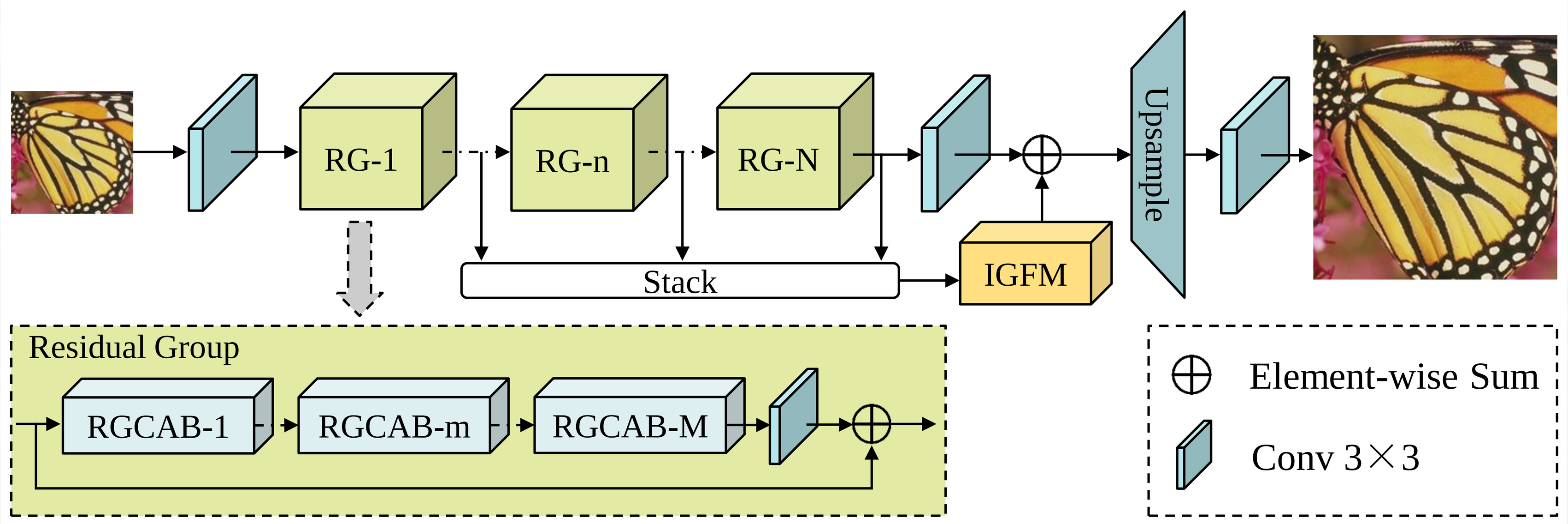

Fig. 1. Network architecture of the proposed global-context attention network (GCAN). The network consists of a set of residual groups, each of which contains several residual global-context attention blocks (RGCABs), and the outputs of all residual groups are stacked together as the input of the inter-group fusion module (IGFM) to explore correlations among group features. Finally, the resulting features are up-sampled to get the final high resolution image.

3. Sub-Modules

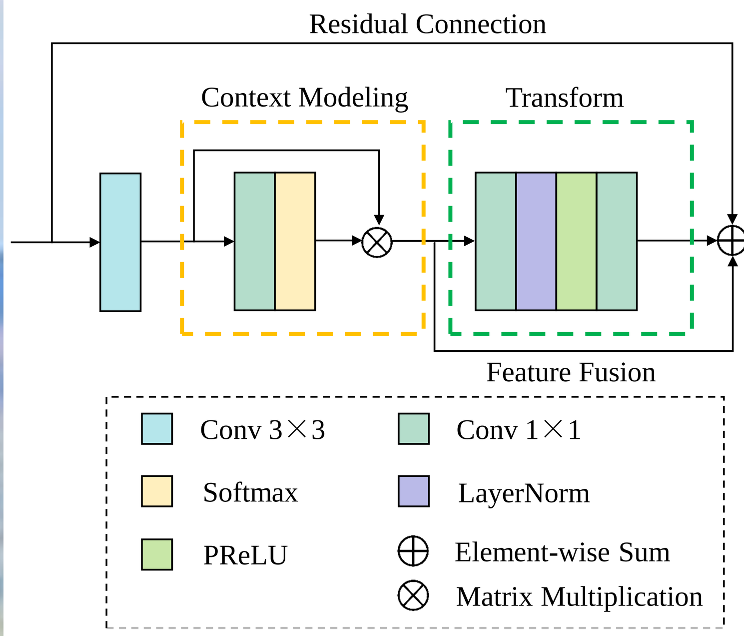

Fig. 2. Residual Global-Context Attention Block (RGCAB).

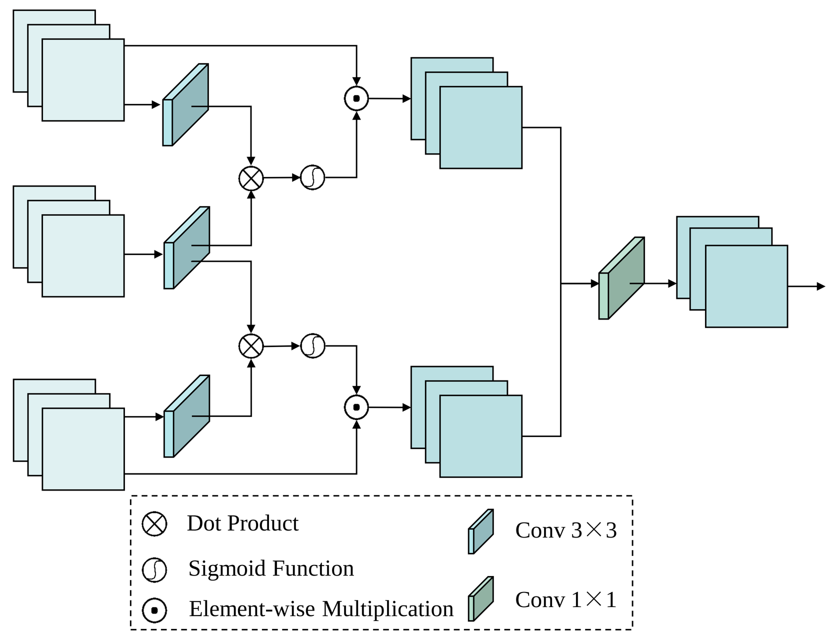

Fig. 3. Inter-Group Fusion Module (IGFM).

4. Datasets & Metrics

Datasets -Training Set: DIV2K

-Testing Set: Set5, Set14, B100, Urban100

Metrics: PSNR, SSIM

5. Experimental Results

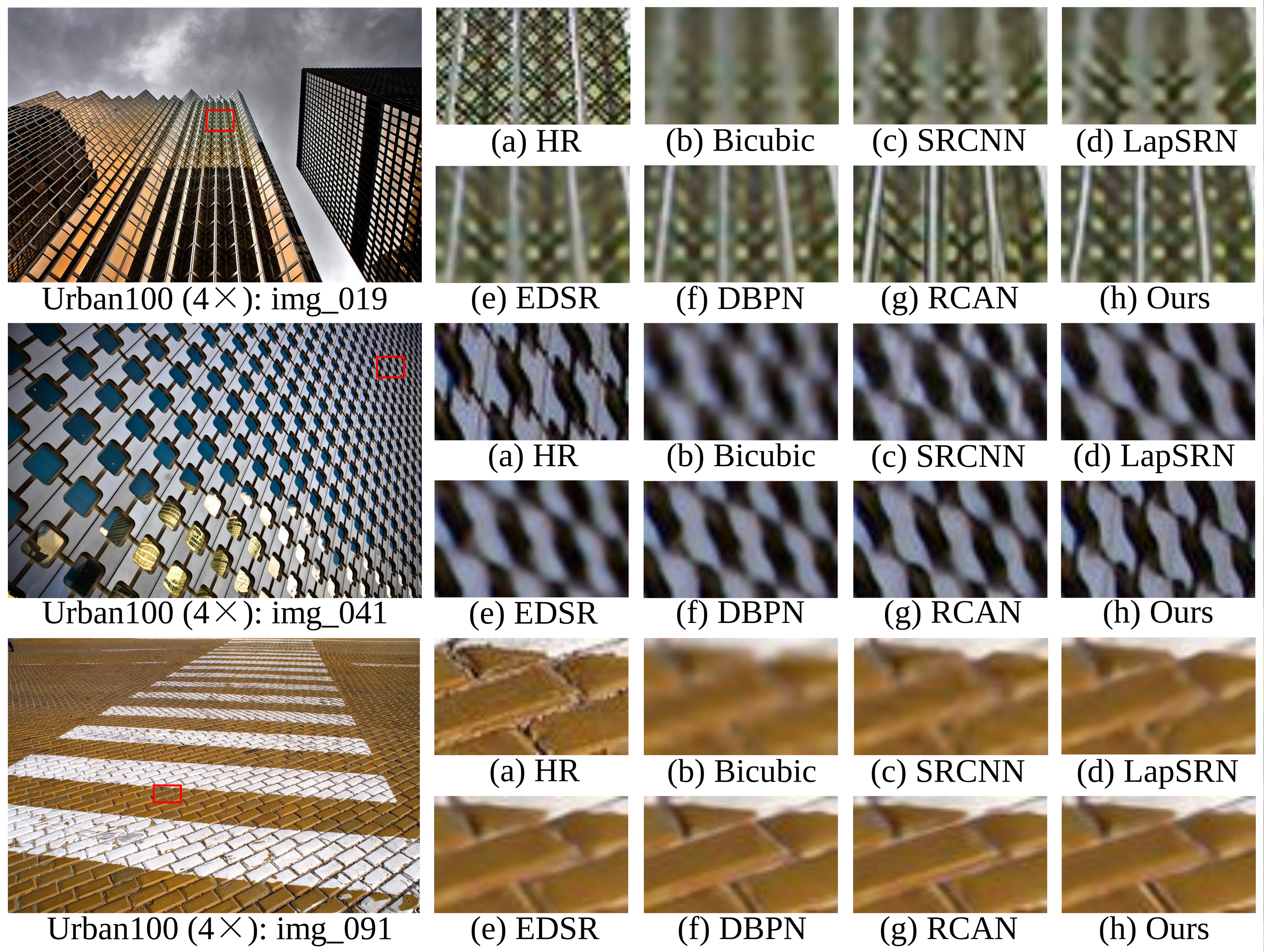

Fig. 4. Visual comparisons for 4× SR on Urban100 datasets.

Table 1. Quantitative results on four datasets: average PSNR/SSIM results for scale factors 2×, 3× and 4×.

Methods	Scale	Set5		Set14		B100		Urban100	
		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Bicubic	×2	33.66	0.9299	30.24	0.8688	29.56	0.8431	26.88	0.8403
SRCNN	×2	36.66	0.9542	32.45	0.9067	31.36	0.8879	29.50	0.8946
LapSRN	×2	37.52	0.9591	33.08	0.9130	31.08	0.8950	30.41	0.9101
EDSR	×2	38.11	0.9602	33.92	0.9195	32.32	0.9013	32.93	0.9351
DBPN	×2	38.09	0.9600	33.85	0.9190	32.27	0.9000	32.55	0.9324
RCAN	×2	38.27	0.9614	34.12	0.9216	32.41	0.9027	33.34	0.9384
SRFBN	×2	38.11	0.9609	33.82	0.9196	33.29	0.9010	32.62	0.9328
GCAN	×2	38.28	0.9615	34.15	0.9217	32.43	0.9029	33.38	0.9386
GCAN+	×2	**38.32**	**0.9617**	**34.22**	**0.9221**	**32.46**	**0.9031**	**33.49**	**0.9392**
Bicubic	×3	30.39	0.8682	27.55	0.7742	27.21	0.7385	24.46	0.7349
SRCNN	×3	32.75	0.9090	29.30	0.8215	28.41	0.7863	26.24	0.7989
LapSRN	×3	33.82	0.9227	29.87	0.8320	28.82	0.7980	27.07	0.8280
EDSR	×3	34.65	0.9280	30.52	0.8462	29.25	0.8093	28.80	0.8653
RCAN	×3	34.74	0.9299	30.65	0.8482	29.32	0.8111	29.09	0.8702
SRFBN	×3	34.70	0.9292	30.51	0.8461	29.24	0.8084	28.73	0.8641
GCAN	×3	34.79	0.9300	30.67	0.8483	29.34	0.8113	29.10	0.8703
GCAN+	×3	**34.85**	**0.9303**	**30.76**	**0.8493**	**29.40**	**0.8120**	**29.25**	**0.8722**
Bicubic	×4	28.42	0.8104	26.00	0.7027	25.96	0.6675	23.14	0.6577
SRCNN	×4	30.48	0.8628	27.50	0.7513	26.90	0.7101	24.52	0.7221
LapSRN	×4	31.54	0.8850	28.19	0.7720	27.32	0.7270	25.21	0.7560
EDSR	×4	32.46	0.8968	28.80	0.7876	27.71	0.7420	26.64	0.8033
DBPN	×4	32.47	0.8980	28.82	0.7860	27.72	0.7400	26.38	0.7946
RCAN	×4	32.63	0.9002	28.87	0.7889	27.77	0.7436	26.82	0.8087
SRFBN	×4	32.47	0.8983	28.81	0.7868	27.72	0.7409	26.60	0.8015
GCAN	×4	32.64	0.9003	28.91	0.7889	27.79	0.7437	26.83	0.8088
GCAN+	×4	**32.72**	**0.9011**	**28.98**	**0.7901**	**27.84**	**0.7450**	**26.98**	**0.8126**

6. Conclusion

A global-context attention network (GCAN) is proposed for single image super-resolution. The network is built by stacking residual global-context attention blocks, which utilizes global context attention to learn long-range spatial correlations and channel interdependencies effectively. We further adopt an inter-group fusion module to explore inter-group feature relations and fuse informative related features, which is conducive to enrich the final outputs of the network. Aided by residual connections, the unified network achieves state-of-the-art performance. Extensive experimental results on several benchmark datasets show the superiority of the proposed network.