Table 2 PSNR and SSIM results of different methods (under configuration I)

表 2 不同方法的 PSNR 和 SSIM 结果(配置 1)

方法	指标	Landmark			GSSR			DEGREE			本文方法		
倍数		2	3	4	2	3	4	2	3	4	2	3	4
平均	PSNR	30.41	29.31	27.71	31.39	29.20	27.69	32.56	29.48	27.85	33.66	30.93	29.35
	SSIM	0.860 3	0.825 8	0.786 3	0.894 1	0.840 1	0.784 5	0.922 4	0.849 0	0.790 9	0.937 0	0.884 2	0.835 0
增益	PSNR	3.25	1.63	1.64	2.27	1.74	1.67	1.10	1.45	1.50	–	–	–
	SSIM	0.070 0	0.050 8	0.048 7	0.042 9	0.036 5	0.050 5	0.007 9	0.035 1	0.044 1	–	–	–

Table 3 PSNR and SSIM results of different methods (under configuration II)

表 3 不同方法的 PSNR 和 SSIM 结果(配置 2)

方法	指标	NE-Cloud			VDSR			本文方法		
倍数		2	3	4	2	3	4	2	3	4
平均	PSNR	32.19	29.47	28.08	33.12	29.90	28.34	33.94	31.28	30.04
	SSIM	0.921 6	0.850 5	0.796 2	0.931 0	0.859 5	0.803 2	0.942 1	0.892 1	0.856 0
增益	PSNR	1.75	1.81	1.96	0.81	1.38	1.70	–	–	–
	SSIM	0.020 5	0.041 7	0.059 8	0.011 1	0.032 6	0.052 8	–	–	–

3.5 主观结果

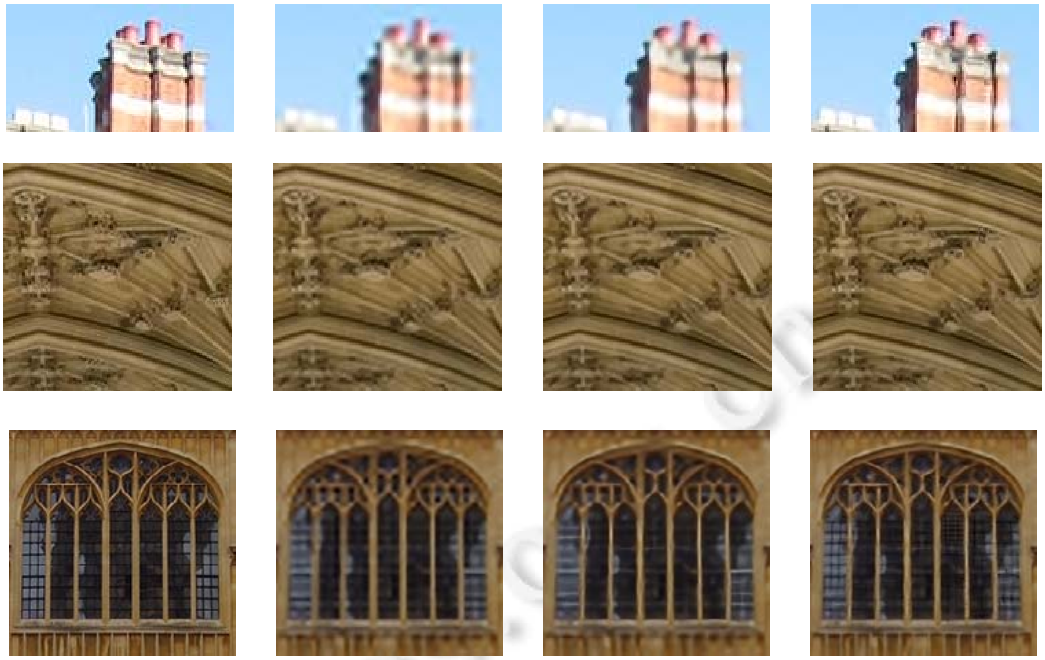
主观结果如图 3 所示.由于 Oxford Building Dataset 中的图像集分辨率较大(1024×768).因此,主观结果仅展示给定完整图像的局部,以便更清晰地比较不同方法重建的高频细节.不同方法按配置 1 和配置 2 在不同放大倍数下的主观结果如图 4 和图 5 所示.

(a) HR (b) DEGREE (c) Landmark (d) GSSR (e) 本文方法

Fig.4 Subjective results of different methods in 3× enlargement on the local regions of testing image ‘h’, ‘d’ and ‘b’ (Configuration I)

图 4 不同方法按配置 1 在 3 倍放大下的主观结果(测试图 h, d 和 b 的局部)

由图 4 和图 5 可以看出,通过在训练图像块集合中加入相似的外部参考图像块,NE-cloud 成功地复原出部分局部边缘.但是,该方法容易丢失部分结构信息,导致失真的重建结果和较低的客观质量.Landmark 成功地复原出部分高频信号,但是,不准确的图像块匹配以及后续的融合导致图像中出现噪音和瑕疵.基于稀疏表示的方法 GSSR 在利用相似参考图像信息时,没有考虑位置信息,因此,更容易引入不准确的匹配图像块,使重建结果中包含更多的噪音.DEGREE 和 VDSR 能够很好地重构出结构信息和部分高频信号.然而,由于未利用外部相似图像的信息,这两种方法无法重建更复杂的高频细节.相比之下,本文方法能够较好地复原图像中的高频信息.由于在设计网络时,同时对内部高频信息重建和外部高频信息补偿进行联合建模,并通过端对端的训练进行优化,本文方法准确地匹配出外部参考图像块,并有效地从中提取出高频信息,重建出视觉上舒适的高分辨率结果.



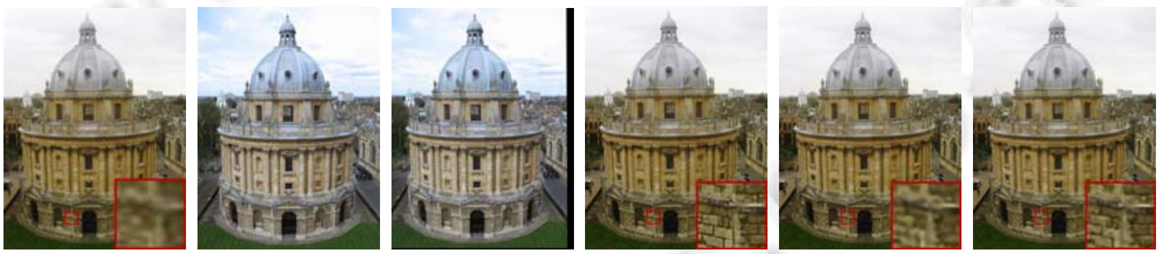
(a) HR (b) NE-Cloud (c) VDSR (d) 本文方法

Fig.5 Subjective results of different methods in 4× enlargement on the local regions of testing image ‘f’, ‘h’ and ‘g’ (Configuration II)

图 5 不同方法按配置 2 在 4 倍放大下的主观结果(测试图 f, h 和 g 的局部)

3.6 叠加分析

图 6 展示了一个重建示例以及各步骤的重建结果.



(a) (b) (c) (d) (e) (f)

Fig.6 Illustrations for the intermediate results of the proposed method

图 6 本文算法各步骤中间结果展示

图 6(a)为输入图像 I^l,图 6(b)为参考图像 I^r,图 6(c)为对齐后的参考图像 $\hat{I}^r$,图 6(d)为高分辨率图像,图 6(e)为中间复原结果 I_t^l,图 6(f)为重建结果 I^h.从图 6 可以看出,仅根据内部高频信息重建得到的中间复原结果(如图 6(e)所示)损失了部分高频信息.经过外部信息补偿后,重建结果(如图 6(f)所示)的高频细节与高分辨率图像(如图 6(d)所示)中原有的高频细节视觉上十分相似.值得一提的是,参考图 6(a)与输入的低分辨率图 6(b)之间的光照、颜色存在巨大的差异,但是由于对内部高频信息重建和外部高频信息补偿进行联合建模,本文方法仍能有效地从中提取高频信息并对内部重建结果进行细节补偿,显著提升了重建性能.

此外,本文验证了所提出训练策略的有效性——对训练数据中的合成参考图像进行光照和颜色的随机扰

动,并对外部高频信息在线补偿路径的输入进行归一化.如表 4 所示,通过在训练中包含光照和颜色扰动,并在外部复原路径中对输入进行归一化,重建结果的质量得以进一步提升,PSNR 的增益为 0.4dB.表 4 中,3 种算法分别为:基础算法、在训练中不包括光照和颜色扰动并在外部复原路径中对输入不进行归一化的本文所提算法以及完整的本文算法.

Table 4 Average PSNR and SSIM results (under configuration I)

表 4 3 种算法的平均 PSNR 和 SSIM 结果(配置 1)

	度量标准	基础算法(DEGREE)	外部复原路径输入未经扰动和归一化	本文方法
平均	PSNR	29.48	30.53	30.93
	SSIM	0.849 0	0.881 3	0.884 2
增益	PSNR	1.45	0.40	–
	SSIM	0.035 1	0.002 9	–

3.7 参考图像个数对重建性能的影响

表 5 展示了本文方法在 3 倍放大下使用不同个数参考图像进行外部补偿的重建性能.其中,使用 0 张参考图像表示不使用外部参考图像的内部重建结果,亦即极深卷积网络的超分辨率重建结果.从结果可以看出,相比于仅使用图像内部的信息,使用 1 张外部参考图像进行外部补偿带来非常大的性能增益,其中,PSNR 增益为 1dB,SSIM 增益为 0.027 1.相比于使用 1 张外部参考图像,使用 2 张外部参考图像能够带来明显的性能增益,PSNR 增益为 0.32dB,SSIM 增益为 0.005 4.继续增加使用外部参考图像的数目,超分辨率重建质量基本保持稳定.

Table 5 Average PSNR and SSIM results of the proposed method using different numbers of external reference images for the external compensated super-resolution with 3 as the scaling factor (under configuration II)

表 5 在 3 倍放大下,本文方法使用不同个数参考图像进行外部补偿重建的 PSNR 和 SSIM 结果(配置 2)

参考图像个数	0	1	2	3	4
PSNR	29.90	30.90	31.22	31.25	31.28
SSIM	0.859 5	0.886 6	0.892 0	0.892 2	0.892 1

3.8 检索精度对重建性能的影响

表 6 展示了本文方法在不使用外部检索图像、检索完全失败、4 张结果中仅有 1 张检索正确、4 张结果中有 1 张检索错误和检索完全正确 5 种情况下的超分辨率重建性能.从结果中可以看出,本文方法十分鲁棒,在全部检索结果都不准确的情况下,只有略微的性能损失,PSNR 损失 0.16dB.此外,只要检索结果中包含正确结果,本文方法就能利用其中的相似信息辅助超分辨率重建,带来显著的性能增益,PSNR 增益为 1.17dB,SSIM 增益为 0.028 8.此外,本文对不使用外部参考图像、外部参考图像全为错误检索结果和外部参考图像中包含 1 张正确检索结果的情况进行视觉对比,如图 7 所示.当检索得到的参考图像与待超分辨图像之间全部不相似时(如图 7(c)所示),重建结果会出现一些噪音或瑕疵,当检索结果中包含至少 1 张正确结果时(如图 7(d)所示),本文方法能够有效排除噪音和错误检索的干扰,恢复出一部分与高分辨率图像相似的高频细节.

Table 6 Average PSNR and SSIM results of the proposed method when there are non-similar images in the retrieved images for the external compensated super-resolution with 3 as the scaling factor (under configuration II)

表 6 在 3 倍放大下,当检索结果存在不相似图像时,本文方法进行外部补偿超分辨率重建的 PSNR 和 SSIM 结果(配置 2)

检索结果中不相似图像的个数	0	1	3	4	不用外部参考图像
PSNR	31.28	31.24	30.91	29.74	29.90
SSIM	0.892 1	0.891 4	0.885 0	0.856 2	0.859 5

图 7(a)为高分辨率图像 I^h,图 7(b)为内部重建结果 I_t^l,图 7(c)为在检索参考图像全部错误情况下的重建结果 I^h,图 7(d)为在检索参考图像包含 1 张正确结果情况下的重建结果 I^h.

(a) (b) (c) (d)

Fig.7 Illustrations for high-frequency detail reconstruction with inaccurately retrieved results

图 7 存在错误检索结果情况下的高频细节重建展示

4 总 结

本文提出了一种基于深度网络、利用在线检索的数据进行高频信息补偿的图像超分辨率重建算法.该网络通过 3 个分支预测高分辨率重建结果:一条旁路直接将输入的低分辨率图像输入到网络的最后一层;高频信息重建路径基于低分辨率图像回归预测高分辨率图像,重建高分辨率图像的主要结构;外部高频信息补偿路径根据内部重建的结果,从在线检索到的相似图像中提取高频细节.在第 2 条路径中,本文在多层特征的测量和约束下,从外部参考图像向重建结果中迁移高频细节.本文方法是端对端可训练的(end-to-end trainable),并对内部重建和外部补偿进行联合建模与优化,从而能够自动地权衡两者利弊,给出最优的重建估计.图像超分辨率重建的实验结果表明,本文方法在主、客观评价中均取得了比当前最佳算法更加优越的性能.

References:

[1] Sun J, Xu Z, Shum HY. Gradient profile prior and its applications in image super-resolution and enhancement. IEEE Trans. on Image Processing, 2011,20(6):1529–1542. [doi: 10.1109/TIP.2010.2095871]

[2] Zuo W, Zhang L, Song C, Zhang D. Texture enhanced image denoising via gradient histogram preservation. In: Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition. 2013. 1203–1210. [doi: 10.1109/CVPR.2013.159]

[3] Katkovnik V, Foi A, Egiazarian K, Astola J. From local kernel to nonlocal multiple-model image denoising. Int'l Journal of Computer Vision, 2010,86(1):1–32. [doi: 10.1007/s11263-009-0272-7]

[4] Dong W, Zhang L, Shi G, Li X. Nonlocally centralized sparse representation for image restoration. IEEE Trans. on Image Processing, 2013,22(4):1620–1630. [doi: 10.1109/TIP.2012.2235847]

[5] Mairal J, Bach F, Ponce J, Sapiro G, Zisserman A. Non-Local sparse models for image restoration. In: Proc. of the IEEE Conf. on Computer Vision. 2009. 2272–2279. [doi: 10.1109/ICCV.2009.5459452]

[6] Marquina A, Osher SJ. Image super-resolution by TV-regularization and Bregman iteration. Journal of Scientific Computing, 2008,37(3):367–382. [doi: 10.1007/s10915-008-9214-8]

[7] Aly HA, Dubois E. Image up-sampling using total-variation regularization with a new observation model. IEEE Trans. on Image Processing, 2005,14(10):1647–1659. [doi: 10.1109/TIP.2005.851684]

[8] Yang J, Wright J, Huang TS, Ma Y. Image super-resolution via sparse representation. IEEE Trans. on Image Processing, 2010,19(11):2861–2873. [doi: 10.1109/TIP.2010.2050625]

[9] Pan Q, Liang Y, Zhang L, Wang SL. Semi-Coupled dictionary learning with applications to image super-resolution and photo-sketch synthesis. In: Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition. 2012. 2216–2223. [doi: 10.1109/CVPR.2012.6247930]

[10] He L, Qi H, Zaretzki R. Beta process joint dictionary learning for coupled feature spaces with application to single image super-resolution. In: Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition. 2013. 345–352. [doi: 10.1109/CVPR.2013.51]

[11] Li Y, Liu J, Yang W, Guo Z. Neighborhood regression for edge-preserving image super-resolution. In: Proc. of the IEEE Int'l Conf. on Acoustics, Speech and Signal Processing. 2015. 1201–1205. [doi: 10.1109/ICASSP.2015.7178160]

[12] Chang H, Yeung DY, Xiong Y. Super-Resolution through neighbor embedding. In: Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition. 2004. 1:I. [doi: 10.1109/CVPR.2004.1315043]

[13] Timofte R, De Smet V, Van Gool L. Anchored neighborhood regression for fast example-based super-resolution. In: Proc. of the IEEE Int'l Conf. on Computer Vision. 2013. 1920–1927. [doi: 10.1109/ICCV.2013.241]

[14] Timofte R, De Smet V, Van Gool L. A+: Adjusted anchored neighborhood regression for fast super-resolution. In: Proc. of the Asian Conf. on Computer Vision. 2014. 111–126. [doi: 10.1007/978-3-319-16817-3_8]

[15] Salvador J, Pérez-Pellitero E. Naive bayes super-resolution forest. In: Proc. of the IEEE Int'l Conf. on Computer Vision. 2015. 325–333. [doi: 10.1109/ICCV.2015.45]

[16] Schulter S, Leistner C, Bischof H. Fast and accurate image upscaling with super-resolution forests. In: Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition. 2015. 3791–3799. [doi: 10.1109/CVPR.2015.7299003]

[17] Dong C, Loy CC, He K, Tang XO. Learning a deep convolutional network for image super-resolution. In: Proc. of the European Conf. on Computer Vision. 2014. 184–199. [doi: 10.1007/978-3-319-10593-2_13]

[18] Liu D, Wang Z, Wen B, Yang JC, Han W, Huang TS. Robust single image super-resolution via deep networks with sparse prior. IEEE Trans. on Image Processing, 2016, 25(7):3194–3207. [doi: 10.1109/TIP.2016.2564643]

[19] Wang Z, Liu D, Yang J, Ha W, Huang T. Deep networks for image super-resolution with sparse prior. In: Proc. of the IEEE Int'l Conf. on Computer Vision. 2015. 370–378. [doi: 10.1109/ICCV.2015.50]

[20] Yang W, Feng J, Yang J, Zhao F, Liu J, Guo Z, Yan S. Deep edge guided recurrent residual learning for image super-resolution. IEEE Trans. on Image Processing, 2017,26(12):5895–5907. [doi: 10.1109/TIP.2017.2750403]

[21] Kim J, Kwon Lee J, Mu Lee K. Accurate image super-resolution using very deep convolutional networks. In: Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition. 2016. 1646–1654. [doi: 10.1109/CVPR.2016.182]

[22] Kim J, Kwon Lee J, Mu Lee K. Deeply-Recursive convolutional network for image super-resolution. In: Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition. 2016. 1637–1645. [doi: 10.1109/CVPR.2016.181]

[23] Timofte R, De Smet V, Van Gool L. Semantic super-resolution: When and where is it useful. Computer Vision and Image Understanding, 2016,142:1–12. [doi: 10.1016/j.cviu.2015.09.008]

[24] Johnson J, Alahi A, Li FF. Perceptual losses for real-time style transfer and super-resolution. In: Proc. of the European Conf. on Computer Vision. 2016. 694–711. [doi: 10.1007/978-3-319-46475-6_43]

[25] Ledig C, Theis L, Huszár F, Caballero J, Cunningham A, Acosta A, Aitke A, Tejani A, Totz J, Wang ZH, Shi WZ. Photo-Realistic single image super-resolution using a generative adversarial network. In: Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition. 2016. 105–114. [doi: 10.1109/CVPR.2017.19]

[26] Yue H, Sun X, Yang J, Wu F. Landmark image super-resolution by retrieving Web images. IEEE Trans. on Image Processing, 2013,22(12):4865–4878. [doi: 10.1109/TIP.2013.2279315]

[27] Li Y, Dong W, Shi G, Xie X. Learning parametric distributions for image super-resolution: Where patch matching meets sparse coding. In: Proc. of the IEEE Int'l Conf. on Computer Vision. 2015. 450–458. [doi: 10.1109/ICCV.2015.59]

[28] Liu J, Yang W, Zhang X, Guo Z. Retrieval compensated group structured sparsity for image super-resolution. IEEE Trans. on Multimedia, 2017,19(2):302–316. [doi: 10.1109/TMM.2016.2614427]

[29] Dong C, Loy CC, Tang X. Accelerating the super-resolution convolutional neural network. In: Proc. of the European Conf. on Computer Vision. 2016. 391–407. https://www.springerprofessional.de/en/accelerating-the-super-resolution-convolutional-neural-network/10708956

[30] Shi W, Caballero J, Huszár F, Totz J, Aitken AP, Bishop R, Rueckert D, Wang ZH. Real-Time single image and video super-resolution using an efficient sub-pixel convolutional neural network. In: Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition. 2016. 1874–1883. [doi: 10.1109/CVPR.2016.207]
[31] Yue H, Sun X, Yang J, Wu F. CID: Combined image denoising in spatial and frequency domains using Web images. In: Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition. 2014. 2933–2940. [doi: 10.1109/CVPR.2014.375]
[32] Liu X, Wu X, Zhou J, Zhao D. Data-Driven sparsity-based restoration of JPEG-compressed images in dual transform-pixel domain. In: Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition. 2015. 5171–5178. [doi: 10.1109/CVPR.2015.7299153]
[33] Zhang Y, Dong W, Deussen O, Huang FY, Li K, Hu BG. Data-Driven face cartoon stylization. In: Proc. of the ACM Conf. and Exhibition on Computer Graphics and Interactive Techniques in Asia. 2014. 1–4. [doi: 10.1145/2669024.2669028]
[34] Wang B, Yu Y, Wong TT, Chen C, Xu YQ. Data-Driven image color theme enhancement. Proc. of the ACM Trans. on Graphics, 2010,29(6):146. [doi: 10.1145/1882261.1866172]
[35] Freeman WT, Liu C. Markov random fields for super-resolution and texture synthesis. Advances in Markov Random Fields for Vision and Image Processing, 2011,1:155–165.
[36] Xiong Z, Xu D, Sun X, Wu F. Example-Based super-resolution with soft information and decision. IEEE Trans. on Multimedia, 2013,15(6):1458–1465. [doi: 10.1109/TMM.2013.2264654]
[37] Yang J, Lin Z, Cohen S. Fast image super-resolution based on in-place example regression. In: Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition. 2013. 1059–1066. [doi: 10.1109/CVPR.2013.141]
[38] Bay H, Ess A, Tuytelaars T, Gool LV. Speeded-Up robust features (SURF). Computer Vision and Image Understanding, 2008, 110(3):346–359. [doi: 10.1016/j.cviu.2007.09.014]
[39] Li FF, Perona P. A Bayesian hierarchical model for learning natural scene categories. In: Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition. 2005,2:524–531. [doi: 10.1109/CVPR.2005.16]
[40] Lowe DG. Distinctive image features from scale-invariant keypoints. Int'l Journal of Computer Vision, 2004,60(2):91–110. [doi: 10.1023/B:VISI.0000029664.99615.94]
[41] Yang J, Wang Z, Lin Z, Cohen S, Huang T. Coupled dictionary training for image super-resolution. IEEE Trans. on Image Processing, 2012,21(8):3467–3478. [doi: 10.1109/TIP.2012.2192127]
[42] Martin D, Fowlkes C, Tal D, Malik J. A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics. In: Proc. of the IEEE Int'l Conf. on Computer Vision. 2001,2: 416–423. [doi: 10.1109/ICCV.2001.937655]
[43] Dong WS, Zhang L, Shi GM, Li X. Nonlocally centralized sparse representation for image restoration. IEEE Trans. on Image Processing, 2013,22(4):1620–1630.
[44] Philbin J, Chum O, Isard M, Sivic J, Zisserman A. Object retrieval with large vocabularies and fast spatial matching. In: Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition. 2007. 1–8. [doi: 10.1109/CVPR.2007.383172]

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