A Review on Self Learning Based Methods for Real World Single Image Super Resolution

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Abstract. Image super resolution (ISR) is one of the popular techniques of image processing to boost the resolution of images. Reconstructing high-resolution (HR) image from low resolution (LR) degraded images results in Single image super resolution (RSISR) reconstruction. In the domain of image processing, it is the lively research topic. This paper covers datasets which are available and assessment metrics for RSISR and method of RSISR based on Self-Learning RSISR [1]. In terms of both reconstruction quality and computational efficiency comparisons are done among representative RSISR methods on datasets. We will discuss challenges on RSISR.

Keywords : Real-world image, Super-resolution, Deep learning, Datasets, Self-learning-based methods.

1 Introduction

Image super resolution (ISR) is having limitations such as unknown degradation, LR-HR images missing paired. Real world images do have problem of degradation like blurring, additive noise and compression artefacts. Compression artefacts are nothing but distortion of media due to lossy compression application. Models trained manually in real-world image datasets often performs poorly. To overcome these limitations some work [2], [3], [4], [5] has been proposed. Still there are some drawbacks in these studies, which will result in difficulty in training and over-perfect assumptions. In fact, it is propitious decision for specific domains, like intelligent surveillance, remote sensing, object tracking, scene rendering and medical imaging to apply SR.

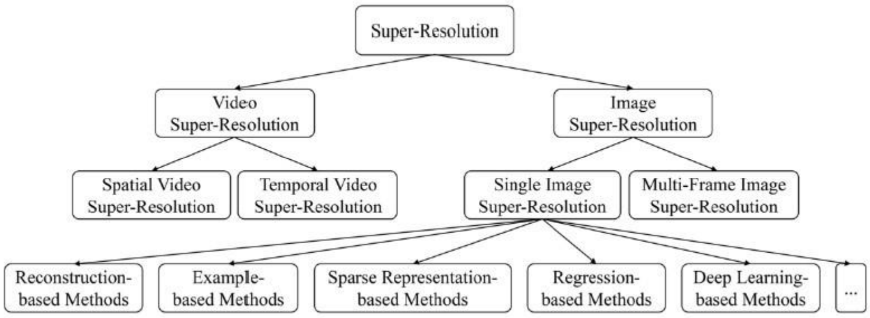

Fig. 1. Existing Super-Resolution Techniques.

Images with higher resolution need upgraded hardware. With recent development in imaging devices and techniques we can achieve required high resolution images but with limitations. (i) Cost is very high because the demand in applications is not stable. (ii) We can get new images with high resolution but not existing images with low resolution with High resolution. This is why super resolution is more flexible and inexpensive.

To train SR models LR images are generated by downsampling RGB images manually with the help of various methods such as bicubic downsampling.

Cameras can capture 12-bit or 14-bit RAW images in reality but due to image signal processors of cameras produces 8-bit RGB images which losses lot of original signals and they have different features as compared to original images taken by the camera like demosaicing, denoising and compression. This is the main reason to use manually downscaled RGB images for SR. Some researcher's doing research to solve this problem. Chen et al. [6] observed relation between field of view in imaging systems and image resolution (R), to conduct real world dataset City100 proposed data acquisition strategies and achieved superior results in his proposed model of image synthesis. Zhang et al. [7] has developed real world image dataset SR_RAW which consist of paired RAW images and LR RGB images with the help of optical zoom of cameras to solve the misalignment problem proposed contextual bilateral loss. On the contrary Xu et al. [8] is generating a realistic training data by image processing simulation and to exploit originally captured radiance information in RAW images dual CNN is developed.

2 Background

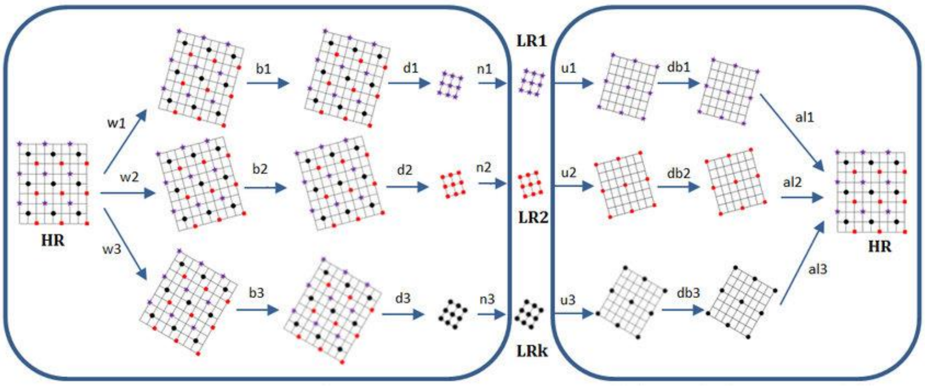

Fig. 2. (a) Generating LR images from HR (b) Basic premise for super-resolution

In the process of generation of LR images from HR images reverse engineering super resolution to obtain reconstructed HR images from multiple LR images. Original HR imae is warped(wk), blurred(bk), downsampled (dk) and noise dded (nk) to generate LR images. A basic super-resolution approach will up-sample, de-blur, align, then combine the LR images to reconstruct the HR image.

Degradation of LR image (Y) from corresponding HR image (X) is represented as follows,

$$Y = DP\ (X, \theta_{DP}) \qquad (1)$$

Where, process of degradation is denoted by DP () defined by parameter set θ_{DP}.

We only have Y i.e., LR image and the degradation parameter θ_{DP} is not known,

SISR recovers desired HR image by inversing the degradation process done in Eq. (1), to get super resolved image from Y which is represented by $\hat{x}$ which is an estimated real HR image X as follows,

$$\hat{x} = SR\ (Y, \theta_R) \qquad (2)$$

Where, SR () is the SR function defined by the parameter set θ_R,

Degradation process DP () and SR process SR () were inverses of each other's. SR (Y, θ_R) must be transformed to the degradation DP(X, θ_{DP}) in order to achieve superior reconstruction performance.

Simulated degradation process mathematically obtained by following equation,

$$Y = SBX + n \qquad (3)$$

Where, B is blurring operation and S is downsampling operation. In general, With the combination of the HR image and a Gaussian kernel blurring is realized. n is assumed to be white Gaussian noise [1].

To generate an LR image, some researchers follow the simple degradation model using the “bicubic” kernel directly to downscale an HR image. By considering learning-based SISR approaches such as RCAN [9], SAN [10], and RFANet [11] the SR reconstruction performance on synthetic LR images is reasonably good. Actually, degradation process is more complex and varying because it is influenced by various factors as compared to commonly used degradation model in simulations. Synthetic LR images and realistic LR observations have large gap between these domains, which causes significant drop in reconstruction performance of most existing SISR algorithms on real world images. To overcome this major drawback, researchers were working on RSISR since several years in various directions including building realistic datasets, SR performance assessment and SR model development.

3 DATASETS

In this section we briefly discuss publicly available datasets. Very few datasets consists of HR image along with LR images almost all datasets consists of only HR image to train and test models. To overcome these challenges more datasets for RSISR have been developed and they are listed below.

Sr. No	Datasets	Published	Synthetic / Realistic	Scale factors	Keywords
1	DIV2KRK	NeurIPS-2019 [12]	Synthetic	*2, *4	DIV2K, Random kernels, Uniform multiplicative noise
2	Real SR	ECCV-2020[14]	Realistic	*2, *3, *4	Focal length adjusting
3	DReal SR	ECCV-2020[14]	Realistic	*2, *3, *4	Focal length adjusting
4	City100	CVPR-2019[15]	Realistic	*2.9, *2.4	Focal length adjusting, shooting distance changing
5	SR-RAW	CVPR-2019[16]	Realistic	*4, *8	Focal length adjusting, RAW data
6	TextZoom	ECCV-2020[17]	Realistic	*2	Text, Recognition
7	SupER	TPAMI-2020 [13]	Realistic	*2, *3, *4	Hardware binning, image sequences

8	Image-Pairs	CVPRW-2020[18]	Realistic	*2	Beam splitter cube, RAW data

Table 1. DATASETS FOR RSISR

3.1 DIV2KRK [12]:

Bell-Kligler et al. [12] built this synthetic testing dataset for blind SR derived from DIV2K [61]. It consists of diverse images of 2K resolution. From the validation set of DIV2K [61] 100 HR images were blurred; with random kernel they are downsampled to get corresponding LR images. Degradation model of DIV2KRK is more complex and random.

3.2 RealSR [14]:

Cai et al. [14] build this real-world dataset for training and testing RSISR models. It has 595 image pairs of HR & LR which is generated through 2 DSLR cameras. Progressive image registration framework is proposed in order to achieve pixel wise registration of images captured at 28mm, 35mm, 50mm and 105mm by Cai et al. [14]. Lens distortion and interested regions of corrected images were cropped using photoshop firstly, real-world HR-LR image pairs can be obtained after this conversion.

3.3 DRealSR [15]:

Wei et al. [81] built real world dataset DrealSR [15] which is having larger scale than RealSR [14]. To capture indoor and outdoor images 5 DSLR cameras were used with different resolutions; for alignment these images SIFT [28] algorithm is used. DRealSR [15] consists of 884(*2), 783(*3), 840(*4) image pairs of LR & HR.

3.4 City100 [16]:

To characterize resolution of field of view FoV with the use of DSLR and smartphones Chen et al. [27] proposed City100 dataset which includes City100, NikonD5500 and iPhoneX. There is a counterbalance between the FoV and resolution for imaging system. If we zoom out the lens, we will get larger FoV but it is with low resolution. But if we zoom in the lens, we can increase the resolution of an image. This is the reason behind adjusting focal length or shooting distance by Chen et al. [27]. And this focal length is 55mm and 18mm kept for taking HR-LR images. Again, for alignment of images SIFT [28] RANSAC [41] algorithms were used. To increase accuracy intensity and rectification of colour is done.

3.5 SR-RAW [17]:

Zhang et al. [17] proposed SR-RAW dataset which consists of different levels of optical zoom RAW images captured for the same scene with different resolutions by adjusting focal length. By using 24-240mm zoom lens seven images of each scene were taken. These seven image sequences were captured in outdoor and indoor scenes with 500 sequences.

3.6 TextZoom [18]:

Wang et al. [18] constructed the TextZoom dataset from RealSR[14] and SR-RAW [16] is the first real scene text SR dataset. Text images in this dataset were cropped from the images of RealSR[14] and SR-RAW[16] including shops, vehicles, gardens, interiors of buildings. TextZoom[18] is developed according to difficulty levels easy, medium and hard. To study text image SR as well as text recognition TextZoom [84] can be utilized.

3.7 SupER [13] :

K¨ohler et al. [24] developed the SupER[13] dataset by hardware binning. Using Basler acA2000-50gm CMOS camera with a f/1.8, 16mm fixed focus lenses more than 80000 images captured from 14 lab scenes with 4 imaging resolutions and 5 levels of compression. To get exact alignment between HR- LR images imaging resolution is adjusted by changing the binning factor, 3 different levels of resolution and binning factors were used to generate LR images corresponding to HR image.

3.8 ImagePairs [18]:

Joze etal. [18] proposed ImagePairs [18] which includes 11421 LR-HR image pairs (LRHRIP) of diverse scenes captured by 5 mega pixel camera (LR) and 20.1 mega pixel HR camera.

To capture same scene images simultaneously with two different cameras a beam splitter cube is used. But due to differences in focal length Joze et al. [30] proposed pixel based aligned LRHRIP with following 4 steps

i. ISP Process: In this process first images captured by LR-HR cameras were converted to colour images.
ii. Distortion: Using camera calibrations tangential and radial distortions were reduced.
iii. Alignment of LR-HR images are done globally and locally.
iv. To improve matching accuracy of image pairs 10% of border is removed. As ImagePairs [18] includes raw images it should be used for ISP and other tasks.

4 Image Quality Assessment

4.1 Peak Signal-to-Noise Ratio (PSNR):

It is one the popular metrics used for quality assessment for image restoration (e.g., SR, denoising, deblocking, and deblurring).

$$\text{PSNR} = 10.\ \log_{10} * \frac{L^2}{MSE} \qquad (4)$$

Where mean squared error MSE is defined as follows,

$$\text{MSE} = \frac{1}{HWC} \left\| \mathrm{Y} - \hat{\mathrm{Y}} \right\|_2^2$$

L equals to 255 in general cases using 8-bit representations.
For pixel level MSE PSNR is the most widely used evaluation metrics. It focuses only on differences between corresponding pixels instead of visual perceptions.

4.2 Information Fidelity Criterion (IFC) [20]:

Based on natural scene statistics the quality of images may be assessed by the information fidelity criterion (IFC) [20]. Characterization of natural images formed by statistics of the space can be done using models like Gaussian Scale Mixture is shown by researchers. Statistics of natural images will be disturbed by distortion and it will make unnatural images. To quantify the mutual information between test image and reference by using natural scenes and distortion models to measure images visual quality. Overall, the IFC [20] performs well for the quality assessment of super-resolved images [23].

4.3 LPIPS [21]:

For referenced based image quality assessment metric is learned metric - Learned Perceptual image patch similarity (LPIPS). By taking difference between reference and test image in a deep feature space LPIPS is achieved, which is good outcome as per human judgements. To fit the Quality-Aware features extracted from images Multivariate Gaussian (MVG) Model is used. To characterize the behaviour of image patches features are included with parameters of Generalized Gaussian Distribution (GGD) and Asymmetric Generalized Gaussian Distribution (AGGD). The distance between two MVG models fitting natural images and evaluated images is used to measure the quality of an image.

4.4 PIQE [22]:

The perception-based quality evaluator (PIQE) is a no-reference image quality assessment metric [22]. To identify distortion and grade quality block level analysis is conducted by dividing test image into non-overlapping blocks. By pooling block level quality scores, a quality of an evaluated images is obtained.

4.5 NRQM [19]:

This is a learned no-reference quality metric (NRQM) for assessing super-resolved images [19]. In this feature extraction is done to predict the perceptual scores of super-resolved image which includes local, global frequency features, and spatial features.

5 METHODS AND TECHNOLOGIES

Fig. 3. RSISR Methods

More focus is given to RSISR as the SR performance on synthetic data is giving better results. Fig 2. Shows existing RSISR techniques grouped into four categories based on their principles and characteristics as degradation modelling- based methods [33]-[43], image pairs-based methods [44]-[55], and self-learning-based methods [39], [56]-[60].

5.1 Self-Learning-based Methods

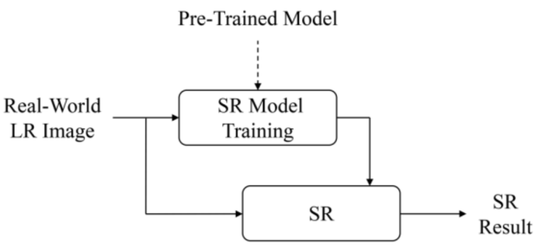

Fig. 4. Self-learning-based SR method

For training SR models existing RSISR methods use paired or unpaired training data which is external dataset. Consistency between testing and training data results in tightly bound SR performance. Characteristics of training data of real-world images are not always consistent. To reduce the impact of inconsistency of training testing on SR performance, information of LR input is exploited to learn image specific SR model as shown in above fig. 3. Shocher et al. [56] developed the Zero-Shot SR (ZSSR) follows self-supervised approach is based on the common property of natural images i.e., cross scale internal recurrence of information. In the testing phase, example pairs extracted from LR test image and its degraded images to train image-specific LR_HR relations by using 8-layer CNN. Data augmentation is adopted while extracting image specific LRHR pairs as there is insufficient training data because of only test image. In order to achieve excellent SR performance on real-world images, ZSSR [56] adapts itself with different testing images with unknown and unideal degradation process. Bell-Kligler et al. [39] proposed to train an image-specific GAN (Kernel GAN) based on the cross-scale recurrency property to model the degradation process (blur kernel) of the input. So, in order to achieve fully self-supervised image-specific RSISR framework by plugin the blur kernel estimation model KernelGAN [39] into reconstruction model ZSSR [56]. Kim et al. [57] developed a unified internal learning-based SR framework DBPI, consisting of an SR network and a downscaling network to jointly train the image-specific degradation and SR networks. To reconstruct LR image from its downscaled version produced by downscaling network, SR network is optimized in the self-supervised training phase of DBPI. Meanwhile to recover the LR input image from its super-resolved version produced by SR network the downscaling network is trained. Similarly, DualSR [58] was proposed by Emad et al. [58] which jointly optimizes image-specific downsampler and relative upsampler. By using the patches from the test image, the DualSR [58] is trained with three losses cycle-consistency, masked interpolation and the adversarial loss which results in [57], [58] complementary training of the image specific degradation and SR network is beneficial to the reconstruction framework.

Due to self-supervised training strategy, self-learning based RSISR approaches such as ZSSR [56], KernelGAN [39], and DBPI [57] has two main limitations. I) Even though larger scale external information was available it is neglected as optimized SR models only uses the internal information. II) Because of online training these methods were very time consuming. Meta-learning is introduced into self-learning-based SR methods to overcome these limitations. Soh et al. [59] proposed the meta-transfer learning for zero-shot SR (MZSR) based on ZSSR [56] which consists of 3 steps large-scale training, meta-transfer learning and meta test.

1) On the large-scale dataset DIV2K [61], large scale training step one trains an 8-layer SR network with pixel wise l_1 loss in order to make it easy training the SR network and the meta-learning.

2) The aim of meta-learning is to find a generic initial point for internal learning by following the Model-Agnostic Meat-Learning [62], model can be adapted quickly to new image conditions within few gradient updates.
3) To generate example pairs for model parameter update, the input image is degraded, and then it is given to updated model to generate SR result, in the met-test phase.

Meta- transfer learning strategy (MZSR) [59] achieves competitive performance in terms of both the quality of the super-resolved image and running time. Reconstruction quality, generalization capability, and processing efficiency was achieved using meta-learning-based SR approaches.

6 CURRENT CHALLENGES AND FUTURE DIRECTIONS

As we seen in section III and IV research on RSISR is positively done still there are some problems need further exploration. In this section we discuss some of the challenges and future work.

6.1 Image Datasets

Dataset is essential when it comes to self-learning equally as SR techniques for any research. In this field of research several datasets were designed but still it is required to develop more datasets focused on realistic image with more accuracy, images captured with different resolutions on same scene.

6.2 SR Algorithms

Still, it is not possible to apply RSISR algorithms to practical applications even though performance was increasing. As there are two major limitations of real-world images suffers from degradation problem therefore it is necessary to adapt RSISR models with ever changing real-world images. Other major limitation is with resources required are very highly configured for large model which is time consuming and also requires more storage space. Hence it is necessary to adapt lightweight design and implementation of SR models.

6.3 Evaluation Criteria

PSNR and SSIM are the two mostly used evaluation metrics for SR with inability of measuring visual quality of super-resolved images accurately. Due to this these metrics were unfit for implementing in practical applications. Hence, more suitable evaluation criteria should be developed for RSISR is crucial and immediate research problem.

Evaluation should consider smoothness preserving for flat areas, details enhancing for textures, sharpening of edges etc. To measure visual quality more accurately and conveniently with automatic model remains a challenge.

7 CONCLUSION

Super resolution of real-world images is getting more attention in recent years. In this paper we have discussed recent super resolution method (self-learning- based algorithms) for realistic images, datasets and assessment metrics for RSISR models training and evaluation. Some challenges should be addressed immediately as discussed in previous section. I am sure that this survey can give better understanding of existing studies for researchers, hope challenges were addressed by researchers in future.

References

[1] Honggang Chen, Xiaohai He, Linbo Qing, Yuanyuan Wu, Chao Ren, and Ce Zhu, “Real-World Single Image Super-Resolution: A Brief Review” in arXiv:2103.

[2] Y. Yuan, S. Liu, J. Zhang, Y. Zhang, C. Dong, and L. Lin, “Unsupervised image super-resolution using cycle-in-cycle generative adversarial networks,” in CVPRW, 2018.

[3] Y. Bei, A. Damian, S. Hu, S. Menon, N. Ravi, and C. Rudin, “New techniques for preserving global structure and denoising with low information loss in single-image super-resolution,” in CVPRW, 2018.

[4] A. Bulat, J. Yang, and G. Tzimiropoulos, “To learn image superresolution, use a gan to learn how to do image degradation first,” in ECCV, 2018.

[5] K. Zhang, W. Zuo, and L. Zhang, “Learning a single convolutional super-resolution network for multiple degradations,” in CVPR, 2018.

[6] C. Chen, Z. Xiong, X. Tian, Z.-J. Zha, and F. Wu, “Camera lens super-resolution,” in CVPR, 2019.

[7] X. Zhang, Q. Chen, R. Ng, and V. Koltun, “Zoom to learn, learn to zoom,” in CVPR, 2019.

[8] X. Xu, Y. Ma, and W. Sun, “Towards real scene super-resolution with raw images,” in CVPR, 2019.

[9] Y. Zhang, K. Li, K. Li, L. Wang, B. Zhong, and Y. Fu, “Image super resolution using very deep residual channel attention networks,” in Proceedings of the European Conference on Computer Vision (ECCV), 2018, pp. 286–301.

[10] T. Dai, J. Cai, Y. Zhang, S.-T. Xia, and L. Zhang, “Second-order attention network for single image super-resolution,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 11 065–11 074.

[11] J. Liu, W. Zhang, Y. Tang, J. Tang, and G. Wu, “Residual feature aggregation network for image super-resolution,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2020.

[12] S. Bell-Kligler, A. Shocher, and M. Irani, “Blind super-resolution kernel estimation using an internal-gan,” in 33rd Conference on Neural Information Processing Systems (NeurIPS), 2019, pp. 284–293.

[13] T. K¨ohler, M. B¨atz, F. Naderi, A. Kaup, A. Maier, and C. Riess, “Toward bridging the simulated-to-real gap: Benchmarking superresolution on real data,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 42, no. 11, pp. 2944–2959, 2020.

[14] P. Wei, Z. Xie, H. Lu, Z. Zhan, Q. Ye, W. Zuo, and L. Lin, “Component divide-and-conquer for real-world image superresolution,” in European Conference on Computer Vision (ECCV), 2020.

[15] C. Chen, Z. Xiong, X. Tian, Z.-J. Zha, and F. Wu, “Camera lens super resolution,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 1652–1660.

[16] X. Zhang, Q. Chen, R. Ng, and V. Koltun, “Zoom to learn, learn to zoom,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 3762–3770.

[17] W. Wang, E. Xie, X. Liu, W. Wang, D. Liang, C. Shen, and X. Bai, “Scene text image super-resolution in the wild,” in European Conference on Computer Vision (ECCV), 2020.

[18] H. Reza Vaezi Joze, I. Zharkov, K. Powell, C. Ringler, L. Liang, A. Roulston, M. Lutz, and V. Pradeep, “ImagePairs: Realistic super resolution dataset via beam splitter camera rig,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2020, pp. 518–519.

[19] C. Ma, C.-Y. Yang, X. Yang, and M.-H. Yang, “Learning a no-reference quality metric for single-image super-resolution,” Computer Vision and Image Understanding, vol. 158, pp. 1–16, 2017.

[20] H. R. Sheikh, A. C. Bovik, and G. De Veciana, “An information fidelity criterion for image quality assessment using natural scene statistics,” IEEE Transactions on Image Processing, vol. 14, no. 12, pp. 2117– 2128, 2005.

[21] R. Zhang, P. Isola, A. A. Efros, E. Shechtman, and O. Wang, “The unreasonable effectiveness of deep features as a perceptual metric,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2018, pp. 586–595.

[22] N. Venkatanath, D. Praneeth, M. C. Bh, S. S. Channappayya, and S. S. Medasani, “Blind image quality evaluation using perception based features,” in 2015 Twenty First National Conference on Communications (NCC), 2015, pp. 1–6.

[23] C.-Y. Yang, C. Ma, and M.-H. Yang, “Single-image super-resolution: A benchmark,” in European Conference on Computer Vision (ECCV), 2014, pp. 372–386.

[24] T. K¨ohler, M. B¨atz, F. Naderi, A. Kaup, A. Maier, and C. Riess, “Toward bridging the simulated-to-real gap: Benchmarking super resolution on real data,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 42, no. 11, pp. 2944–2959, 2020.

[25] J. Cai, H. Zeng, H. Yong, Z. Cao, and L. Zhang, “Toward real-world single image super-resolution: A new benchmark and a new model,” in Proceedings of the IEEE International Conference on Computer Vision (ICCV), 2019, pp. 3086–3095.

[26] P. Wei, Z. Xie, H. Lu, Z. Zhan, Q. Ye, W. Zuo, and L. Lin, “Component divide-and-conquer for real-world image super resolution,” in European Conference on Computer Vision (ECCV), 2020.

[27] C. Chen, Z. Xiong, X. Tian, Z.-J. Zha, and F. Wu, “Camera lens super resolution,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 1652–1660.

[28] D. G. Lowe, “Distinctive image features from scale-invariant key points,” International Journal of Computer Vision, vol. 60, no. 2, pp. 91–110, 2004.

[29] W. Wang, E. Xie, X. Liu, W. Wang, D. Liang, C. Shen, and X. Bai, “Scene text image super-resolution in the wild,” in European Conference on Computer Vision (ECCV), 2020.

[30] H. Reza Vaezi Joze, I. Zharkov, K. Powell, C. Ringler, L. Liang, A. Roulston, M. Lutz, and V. Pradeep, “ImagePairs: Realistic super resolution dataset via beam splitter camera rig,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2020, pp. 518–519.

[31] X. Xu, Y. Ma, and W. Sun, “Towards real scene super-resolution with raw images,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 1723–1731.

[32] X. Xu, Y. Ma, W. Sun, and M.-H. Yang, “Exploiting raw images for real-scene super-resolution,” IEEE Transactions on Pattern Analysis and Machine Intelligence, 2020.

[33] W.-Z. Shao and M. Elad, “Simple, accurate, and robust nonparametric blind super-resolution,” in International Conference on Image and Graphics (ICIG), 2015, pp. 333–348.

[34] W.-Z. Shao, Q. Ge, L.-Q. Wang, Y.-Z. Lin, H.-S. Deng, and H.-B. Li, “Nonparametric blind super-resolution using adaptive heavy-tailed priors,” Journal of Mathematical Imaging and Vision, vol. 61, no. 6, pp. 885–917, 2019.

[35] J. Gu, H. Lu, W. Zuo, and C. Dong, “Blind super-resolution with iterative kernel correction,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 1604– 1613.

[36] V. Cornillere, A. Djelouah, W. Yifan, O. Sorkine-Hornung, and C. Schroers, “Blind image super-resolution with spatially variant degradations,” ACM Transactions on Graphics, vol. 38, no. 6, pp. 1–13, 2019.

[37] Y. Huang, S. Li, L. Wang, T. Tan et al., “Unfolding the alternating optimization for blind super resolution,” in 34th Conference on Neural Information Processing Systems (NeurIPS), 2020.

[38] T. Michaeli and M. Irani, “Nonparametric blind super-resolution,” in Proceedings of the IEEE International Conference on Computer Vision (ICCV), 2013, pp. 945–952.

[39] S. Bell-Kligler, A. Shocher, and M. Irani, “Blind super-resolution kernel estimation using an internal-gan,” in 33rd Conference on Neural Information Processing Systems (NeurIPS), 2019, pp. 284–293.

[40] A. Bulat, J. Yang, and G. Tzimiropoulos, “To learn image superresolution, use a gan to learn how to do image degradation first,” in Proceedings of the European Conference on Computer Vision (ECCV), 2018, pp. 185–200.

[41] M. A. Fischler and R. C. Bolles, “Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography,” Communications of the ACM, vol. 24, no. 6, pp. 381–395, 1981.

[42] J. Xiao, H. Yong, and L. Zhang, “Degradation model learning for real-world single image super-resolution,” in Proceedings of the Asian Conference on Computer Vision (ACCV), 2020.

[43] X. Ji, Y. Cao, Y. Tai, C. Wang, J. Li, and F. Huang, “Real-world super resolution via kernel estimation and noise injection,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2020, pp. 466–467.

[44] Y. Yuan, S. Liu, J. Zhang, Y. Zhang, C. Dong, and L. Lin, “Unsupervised image super-resolution using cycle-in-cycle generative adversarial networks,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2018, pp. 701–710.

[45] Y. Zhang, S. Liu, C. Dong, X. Zhang, and Y. Yuan, “Multiple cyclein- cycle generative adversarial networks for unsupervised image super resolution,” IEEE Transactions on Image Processing, vol. 29, pp. 1101–1112, 2020.

[46] G. Kim, J. Park, K. Lee, J. Lee, J. Min, B. Lee, D. K. Han, and H. Ko, “Unsupervised real-world super resolution with cycle generative adversarial network and domain discriminator,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2020, pp. 456–457.

[47] S. Maeda, “Unpaired image super-resolution using pseudo supervision,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2020, pp. 291–300.

[48] K. Prajapati, V. Chudasama, H. Patel, K. Upla, R. Ramachandra, K. Raja, and C. Busch, “Unsupervised single image super-resolution network (USISResNet) for real-world data using generative adversarial network,” in Proceedings of the IEEE Conference on Computer Vision

and Pattern Recognition Workshops (CVPRW), 2020, pp. 464–465.

[49] T. Zhao, W. Ren, C. Zhang, D. Ren, and Q. Hu, “Unsupervised degradation learning for single image super-resolution,” arXiv preprint arXiv:1812.04240, 2018.

[50] C. You, G. Li, Y. Zhang, X. Zhang, H. Shan, M. Li, S. Ju, Z. Zhao, Z. Zhang, W. Cong et al., “CT super-resolution gan constrained by the identical, residual, and cycle learning ensemble (GAN-CIRCLE),” IEEE Transactions on Medical Imaging, vol. 39, no. 1, pp. 188–203, 2020.

[51] M. Fritsche, S. Gu, and R. Timofte, “Frequency separation for real-world super-resolution,” in IEEE International Conference on Computer Vision Workshop (ICCVW), 2019, pp. 3599–3608.

[52] R. Muhammad Umer, G. Luca Foresti, and C. Micheloni, “Deep generative adversarial residual convolutional networks for real-world super-resolution,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2020, pp. 438–439.

[53] M. S. Rad, T. Yu, C. Musat, H. K. Ekenel, B. Bozorgtabar, and J.-P. Thiran, “Benefiting from bicubically down-sampled images for learning real-world image

super-resolution,” in Proceedings of the IEEE Winter Conference on Applications of Computer Vision (WACV), 2021, pp. 1590–1599.

[54] A. Lugmayr, M. Danelljan, and R. Timofte, “Unsupervised learning for real-world super-resolution,” in IEEE International Conference on Computer Vision Workshop (ICCVW), 2019, pp. 3408–3416.

[55] S. Chen, Z. Han, E. Dai, X. Jia, Z. Liu, L. Xing, X. Zou, C. Xu, J. Liu, and Q. Tian, “Unsupervised image super-resolution with an indirect supervised path,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2020,

pp. 468–469.

[56] A. Shocher, N. Cohen, and M. Irani, ““Zero-Shot” super-resolution using deep internal learning,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2018, pp. 3118– 3126.

[57] J. Kim, C. Jung, and C. Kim, “Dual back-projection-based internal learning for blind super-resolution,” IEEE Signal Processing Letters, vol. 27, pp. 1190–1194, 2020.

[58] M. Emad, M. Peemen, and H. Corporaal, “DualSR: Zero-shot dual learning for real-world super-resolution,” in Proceedings of the IEEE Winter Conference on Applications of Computer Vision (WACV), 2021, pp. 1630–1639.

[59] J. W. Soh, S. Cho, and N. I. Cho, “Meta-transfer learning for zero-shot super-resolution,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2020, pp. 3516–3525.

[60] S. Park, J. Yoo, D. Cho, J. Kim, and T. H. Kim, “Fast adaptation to super-resolution networks via meta-learning,” in European Conference on Computer Vision (ECCV), 2020.

[61] E. Agustsson and R. Timofte, “NTIRE 2017 challenge on single image super-resolution: Dataset and study,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2017, pp. 126–135.

[62] C. Finn, P. Abbeel, and S. Levine, “Model-agnostic meta-learning for fast adaptation of deep networks,” in International Conference on Machine Learning (ICML), 2017.