Real-World Single Image Super-Resolution: A Brief Review
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Abstract—Single image super-resolution (SISR), which aims to reconstruct a high-resolution (HR) image from a low-resolution (LR) observation, has been an active research topic in the area of image processing in recent decades. Particularly, deep learning-based super-resolution (SR) approaches have drawn much attention and have greatly improved the reconstruction performance on synthetic data. Recent studies show that simulation results on synthetic data usually overestimate the capacity to super-resolve real-world images. In this context, more and more researchers devote themselves to develop SR approaches for realistic images. This article aims to make a comprehensive review on real-world single image super-resolution (RSISR). More specifically, this review covers the critical publicly available datasets and assessment metrics for RSISR, and four major categories of RSISR methods, namely degradation modeling-based RSISR, image pairs-based RSISR, domain translation-based RSISR, and self-learning-based RSISR. Comparisons are also made among representative RSISR methods on benchmark datasets, in terms of both reconstruction quality and computational efficiency. Besides, we discuss challenges and promising research topics on RSISR.

Index Terms—Super-resolution, Real-world image, Deep learning,Datasets, Assessment Metrics, Review

I. INTRODUCTION

HIGH-RESOLUTION (HR) images are desired urgently in many application areas such as intelligent surveillance, medical imaging, and remote sensing. To obtain images with higher resolution, a natural idea is to upgrade the hardware (e.g., the imaging system). Although recent years have witnessed the obvious progress of imaging devices and techniques, this kind of approach has two main limitations: (i) It is inflexible and costly because the demand in practical applications is constantly changing. (ii) It can be used only for capturing new HR images, but not for enhancing the resolution of existing low-resolution (LR) images. Compared to the hardware upgrade-based “hard” solution, the signal processing-based “soft” image resolution enhancement known as super-resolution (SR) is more flexible and economical. With the SR techniques that reconstruct a higher resolution output from the LR observation, we can obtain images with the resolution beyond the limit of imaging systems, thereby benefiting the subsequent analysis and understanding tasks such as segmentation [1]–[4], detection [5]–[7], and recognition [8]–[10].

In general, as presented in Fig. 1, existing SR techniques can be grouped into two categories according to the LR input and the reconstructed HR output, i.e., video super-resolution (VSR) [11]–[27] and image super-resolution (ISR) [28]–[78]. On the whole, VSR aims to improve the spatial resolution (known as spatial VSR) [11]–[19] or the frame rate (known as temporal VSR) [20]–[27] of the observed video. ISR can be further classified into multi-frame image super-resolution (MISR) [28]–[35] and single image super-resolution (SISR) [36]–[78]. MISR refers to reconstructing an HR image via fusing the complementary information in a series of correlated images of the same scene [28]–[35], while SISR generates an HR image from one LR observation [36]–[78]. In terms of application scenarios, SISR is more practical than MISR and VSR because it is much less demanding on the input, which is one reason why SISR attracts wider attention. A variety of SISR methods have been proposed in the past decades, mainly including reconstruction-based [36]–[45], example-based [46]–[52], sparse representation-based [53]–[59], regression-based [61]–[66], and deep learning-based approaches [67]–[78], etc. Particularly, the deep learning-based SISR methods [67]–[78] developed in recent years take the SR performance on synthetic LR images (e.g., bicubically downsampled images) to a new level.

Nevertheless, previous research [79] shows that the actual SR ability of most existing SISR methods may be overestimated based only on synthetic data due to the domain gap between synthetic and realistic data. In other words, compared to the promising SR results on synthetic test images, the SR performance would degrade significantly on real-world images, thus hindering the practical applications of SISR.
algorithms. To address this problem, some researchers have shifted their focus to real-world single image SR (RSISR) over the past couple of years, and a series of studies involving real-world dataset collection [79–87]. SR models for real-world images [79–115], and SR result assessment [116–119] have been conducted. Meanwhile, several challenges on RSISR have been organized in conjunction with the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), IEEE International Conference on Computer Vision (ICCV), and European Conference on Computer Vision (ECCV) to attract more attention and promote the development of RSISR techniques [120–123]. It is exciting to see that the studies on RSISR are becoming more targeted and the SR performance on real-world images is improved increasingly.

In this work, we mainly give an overview of recent RSISR algorithms and relevant studies. There are several works concerning the overview of imaging and video SR techniques. For example, Yue et al. [124] make a summary of the techniques, applications and future of image SR. Considering that deep learning has been widely employed to address SR over the past few years, more recently Yang et al. [125], Wang et al. [126], and Liu et al. [127] review deep learning-based image/video SR methods. However, this work is the first attempt to make an overview of RSISR techniques to the best of our knowledge. The main contributions of this review are four-fold: (i) We comprehensively review the studies on RSISR, including datasets, assessment metrics, technologies and methods, etc. (ii) We present a taxonomy for existing RSISR methods according to their primary principles. (iii) We compare the reconstruction accuracy and efficiency of representative RSISR algorithms on benchmark datasets. (iv) We further discuss current challenges and future research directions for RSISR.

The rest of this review is organized as follows. The background of RSISR is briefly introduced in Section II. In Section III, the datasets and assessment metrics for RSISR are described. Section IV reviews RSISR technologies and methods by category. The comparisons among representative RSISR algorithms are presented in Section V. In Section VI, we analyze current challenges and future research directions of RSISR. Finally, Section VII concludes this work.

II. BACKGROUND

SISR refers to reconstructing an HR image from an LR observation. Given an LR image \( Y \), it is generally assumed to be degraded from a corresponding HR image \( X \), which can be represented as

\[
Y = D(X, \theta_D)
\]

(1)

where \( D(\cdot) \) denotes the degradation process defined by the parameter set \( \theta_D \). Note that in a real scenario, the degradation parameter \( \theta_D \) is unknown, and all we have is the LR image \( Y \). SISR aims at recovering a good estimate of the potential HR image via reversing the degradation process shown in Eq. (1), which can be formulated as

\[
\hat{X} = R(Y, \theta_R)
\]

(2)

where \( R(\cdot) \) represents the SR function and \( \theta_R \) is the corresponding parameter set. \( \hat{X} \) is the super-resolved image from \( Y \), i.e., an estimate of the real HR image \( X \).

Apparently, the SR process and degradation process are the inverses of each other. Thus, for obtaining excellent reconstruction performance, the SR function \( R(Y, \theta_R) \) should be adapted to the degradation \( D(X, \theta_D) \). In the literature, some researchers [36–45] approximate the degradation via blurring, downsampling, and noise injection. Mathematically, the simulated degradation process is as follows

\[
Y = SBX + n
\]

(3)

where \( B \) and \( S \) denote the operations of blurring and downsampling, respectively. In general, the blurring is realized via convolving the HR image with a Gaussian kernel. \( n \) represents the additive noise, which is usually assumed to be white Gaussian noise. Part of works [61–78] adopt a simpler degradation model, i.e., directly downscaling an HR image using the “bicubic” kernel to generate corresponding LR image. For comparison and evaluation, most existing SR methods are developed and validated on synthetic LR images generated by degradation simulations. Overall, the SR reconstruction performance on synthetic LR images is rather good, especially for deep learning-based SISR approaches such as RCAN [73], SAN [75], and RFA-Net [77].

Compared with the commonly used degradation model in simulations, the actual degradation in real-world scenarios is more complex and varying because it can be affected by a number of factors (e.g., imaging system and imaging environment). In other words, the degradation model used in simulations may not match that suffered by real-world images, which results in the domain gap between synthetic LR images and realistic LR observations. For this primary reason, the reconstruction performance of most existing SISR algorithms drops significantly on real-world images. To enhance quality of super-resolving real-world images, some researchers have been working on RSISR from different perspectives in the past several years, including realistic dataset building, SR model development, SR performance assessment, etc.

III. DATASETS AND ASSESSMENT METRICS

Training/testing datasets and assessment metrics are the cornerstones of the SISR. In this section, we briefly introduce the relevant datasets and assessment metrics.

A. Datasets for RSISR

For the training and testing of SISR models, the widely used datasets include DIV2K [128], BSDS500 [129], T91 [53], Set5 [130], Set14 [54], Urban100 [50], Manga109 [131], etc. Most of these datasets only contain HR images. In this case, we need to generate LR counterparts based on the assumed degradation model (e.g., “bicubic” kernel-based downsampling), both for model training and testing. Therefore, these datasets are not quite suitable for the study of RSISR due to the significant discrepancy between the assumed degradation model and the real one. To address this problem, some more targeted datasets for RSISR have been constructed.
from the images captured at 105mm are used as HR references, and the corresponding regions cropped from the images taken at 28mm, 35mm, and 50mm are aligned to generate LR counterparts via iteratively optimizing the parameters of affine transformation and luminance adjustment. After convergence, real-world LR-HR image pairs can be obtained.

3) DRealSR [81]: The real-world dataset DRealSR built by Wei et al. [81] is similar to RealSR [80], with a larger scale. More specifically, five DLSR cameras (i.e., Sony, Canon, Olympus, Nikon, and Panasonic) are used to capture images at four resolutions in outdoor and indoor scenes (e.g., buildings, offices, plants, posters, etc.). The SIFT algorithm [132] is adopted to align the images with different resolutions. In total, DRealSR [81] contains 884, 783, and 840 LR-HR image pairs for ×2, ×3, and ×4 SR, respectively.

4) City100 [82]: The City100 dataset proposed by Chen et al. [82] includes City100_NikonD5500 and City100_iPhoneX, which characterize the resolution and field-of-view (FoV) degradation under DSLR and smartphone cameras, respectively. As is well known, there is a tradeoff between the resolution and FoV for imaging systems. An image with a larger FoV but a lower resolution can be obtained when zooming out the lens, while the image resolution can be enhanced at the expense of a reduced FoV when zooming in the lens. Therefore, Chen et al. propose [82] to adjust the focal length or shooting distance to capture images of the same scene with different resolutions. 100 postcards of different city scenes are used as imaging subjects. For the City100_NikonD5500 dataset taken by NikonD5500, HR and LR images are captured at the focal length of 55mm and 18mm, respectively. The HR and LR images of the same scene are first spatially aligned based on SIFT key-points [132] and RANSAC [133]. Further, intensity and color rectification is conducted to improve the accuracy of alignment. The main distinction between City100_iPhoneX and City100_NikonD5500 is that City100_iPhoneX is captured by iPhone X via changing the shooting distance.

5) SR-RAW [83]: The SR-RAW dataset proposed by Zhang et al. [83] is composed of pairs of RAW images taken at different levels of optical zoom. The SR-RAW [83] is similar to RealSR [80] mentioned above in terms of the way to capture images of the same scene with different resolutions, i.e., adjusting the focal length. For SR-RAW [83], seven images of each scene are taken under seven different optical zoom settings using a 24-240mm zoom lens (i.e., Sony FE 24-240mm). In total, 500 seven-image sequences are collected in outdoor and indoor scenes. For image registration, the Euclidean motion model is applied to describe the relationship between the images with different resolutions and it is optimized by minimizing the enhanced correlation coefficient as in [134]. Unlike the RealSR built by Cai et al. [80], SR-RAW [83] contains both raw sensor

| Datasets             | Published          | Synthetic / Realistic | Scale Factors | Keywords                      |
|---------------------|--------------------|-----------------------|---------------|-------------------------------|
| DIV2KRK             | NeurIPS-2019       | Synthetic             | ×2, ×4        | DIV2K, Random kernels, Uniform multiplicative noise |
| RealSR              | ICCV-2019          | Realistic             | ×2, ×3, ×4    | Focal length adjusting         |
| DRealSR             | ECCV-2020          | Realistic             | ×2, ×3, ×4    | Focal length adjusting         |
| City100             | CVPR-2019          | Realistic             | ×2.9, ×2.4    | Focal length adjusting, Shooting distance changing |
| SR-RAW              | CVPR-2019          | Realistic             | ×4, ×8        | Focal length adjusting, RAW data |
| TextiZoom           | ECCV-2020          | Realistic             | ×2            | Text, Recognition              |
| SupER               | TPAMI-2020         | Realistic             | ×2, ×3, ×4    | Hardware binning, Image sequences |
| ImagePairs          | CVPRW-2020         | Realistic             | ×2            | Beam-splitter cube, RAW data   |

1DIV2KRK [94] is available at [http://www.wisdom.weizmann.ac.il/~vision/kernelgan/](http://www.wisdom.weizmann.ac.il/~vision/kernelgan/)

2RealSR [80] is available at [https://github.com/csjcai/RealSR](https://github.com/csjcai/RealSR)

3DRealSR [81] is available at [https://github.com/sierzrw5/Component-Divide-and-Conquer-for-Real-World-Image-Super-Resolution](https://github.com/sierzrw5/Component-Divide-and-Conquer-for-Real-World-Image-Super-Resolution)

4City100 [82] is available at [https://github.com/ngche/CameraSR](https://github.com/ngche/CameraSR)

5SR-RAW [83] is available at [https://ceciliavision.github.io/project-pages/project-zoom.html](https://ceciliavision.github.io/project-pages/project-zoom.html)
data and RGB images because it is used for SR from raw data. That is, instead of the LR RGB image, its raw sensor data is used as the input to reconstruct the corresponding HR RGB image. Actually, the reconstruction process covers demosaicing, denoising, SR, etc. Compared with 8-bit RGB images, as pointed out in [83], raw sensor data generally contains more useful information for SR.

6) TextZoom [84]: The TextZoom derived from RealSR [80] and SR-RAW [83] is the first real scene text SR dataset constructed by Wang et al. [84]. More specifically, the text images in TextZoom [84] are cropped from the images in RealSR [80] and SR-RAW [83], including various natural scenes such as shops, street views, and vehicle interiors. The content, direction, and focal length of each LR-HR text image pair in TextZoom are provided in the annotation process. Moreover, TextZoom [84] comprises three subsets according to difficulty levels, namely easy, medium, and hard. Thanks to the well-organized annotations, TextZoom [84] can be utilized to study text image SR as well as text recognition.

7) SupER [79]: The SupER is built by Köhler et al. [79] via hardware binning. More specifically, more than 80,000 images are taken from 14 lab scenes at four imaging resolutions and five compression levels, using a Basler acA2000-50gm CMOS camera with a 5 MP and an HR camera (20.1 MP), respectively. More specifically, a beam-splitter cube is used to make the two cameras have different focal lengths, the LR and HR images are first converted to color images via applying the following four steps: ISP, image undistortion, demosaicing, denoising, etc. Then, distortions (e.g., radial distortions) caused by cameras are reduced via camera calibration. Further, LR and HR images are aligned globally and locally. Finally, 10% of the border is removed from each image to improve the matching accuracy of image pairs.

8) ImagePairs [85]: The ImagePairs proposed by Joze et al. [85] includes 11,821 LR-HR image pairs of diverse scenes, in which LR and HR images are captured by an LR camera (5 MP) and an HR camera (20.1 MP), respectively. More specifically, a beam-splitter cube is used to make the two cameras capture images of the same scene simultaneously. Due to the difference in focal length, the LR and HR cameras have different perspectives. Therefore, Joze et al. [85] propose to generate pixel-wise aligned LR-HR image pairs via applying the following four steps: ISP, image undistortion, pair alignment, and margin cropping. The raw data collected by LR and HR cameras are first converted to color images in the ISP process. Then, distortions (e.g., tangential and radial distortions) caused by cameras are reduced via camera calibration. Further, LR and HR images are aligned globally and locally. Finally, 10% of the border is removed from each image to improve the matching accuracy of image pairs.

Addition to SR, ImagePairs [85] may be used for ISP and other tasks as it includes raw images.

B. Assessment Metrics for Super-Resolved Images

In general, the quality assessment of super-resolved images is two-fold, i.e., human perception-based subjective evaluation and quality metrics-based objective evaluation. Overall, the former is more direct and more in agreement with the practical need. However, subjective evaluation suffers the following limitations. (i) The assessment result is readily affected by personal preferences. (ii) The evaluation process is often costly and cannot be automated. By contrast, objective evaluation is more convenient to use, although the results by different assessment metrics may not be necessarily consistent with each other as well as subjective evaluation. Table II reports commonly used metrics for evaluating the objective quality of super-resolved images, including PSNR, SSIM [135], IFC [136], LPIPS [137], NIQE [138], PIQE [139], and NRQM [116]. For the description, let $X \in \mathbb{R}^{H \times W \times C}$ and $\hat{X} \in \mathbb{R}^{H \times W \times C}$ denote the ground truth image and the super-resolved image, respectively. $H$, $W$, and $C$ denote width, height, and number of components, respectively.

1) PSNR: Peak signal-to-noise ratio (PSNR) is the most widely used full-reference objective quality assessment metric for image restoration (e.g., SR, denoising, deblurring, and deblurring). Given $\hat{X}$ and $X$, the PSNR is defined as

$$PSNR = 10 \cdot \log_{10}(\frac{L^2}{MSE}) \quad (4)$$

where $MSE = \frac{1}{H \cdot W \cdot C} \| X - \hat{X} \|_2^2$ denotes the mean squared error (MSE) between $X$ and $\hat{X}$, and $L$ represents the maximum pixel value (i.e., 255 for 8-bit images). It can be seen from Eq. 4 that PSNR is more concerned with the proximity between corresponding pixels in $X$ and $\hat{X}$, which results in the low consistency with perceptual quality in some cases.

2) SSIM [135]: The structure similarity index (SSIM) [135] is a full-reference objective quality assessment metric that measures structural similarity. More specifically, the

| Metrics | Published | Full/No-reference | Keywords |
|---------|-----------|-------------------|----------|
| PSNR   |           | Full-reference    | Mean squared error |
| SSIM   | TIP-2004 [135] | Full-reference | Structure similarity, Luminance, Contrast, Structures |
| IFC    | TIP-2005 [136] | Full-reference | Nature scene statistics, Gaussian scale mixtures |
| LPIPS  | CVPR-2018 [137] | Full-reference | Deep features, Human perceptual similarity |
| NIQE   | SPI-2012 [138] | No-reference | Quality-aware features, Multivariate Gaussian model |
| PIQE   | NCC-2015 [139] | No-reference | Perceptually significant spatial regions, Block level distortion map |
| NRQM   | CVIU-2017 [116] | No-reference | Statistical features, Regression forests, Linear regression model |

TABLE II

AN OVERVIEW OF WIDELY USED ASSESSMENT METRICS FOR RSISR.
comparisons are jointly performed in the aspects of luminance, contrast, and structures as
\[
SSIM = \left[ l(X, \hat{X}) \right]^{\alpha} \left[ c(X, \hat{X}) \right]^{\beta} \left[ s(X, \hat{X}) \right]^{\gamma}
\] (5)
where \( l(X, \hat{X}) = \frac{2\mu_X\mu_{\hat{X}} + C_1}{\mu_X^2 + \mu_{\hat{X}}^2 + C_1} \), \( c(X, \hat{X}) = \frac{2\sigma_X\sigma_{\hat{X}}}{\sigma_X^2 + \sigma_{\hat{X}}^2 + C_2} \), and \( s(X, \hat{X}) = \frac{\sigma_{X\hat{X}}}{\sigma_X\sigma_{\hat{X}} + C_3} \). \( \alpha, \beta, \) and \( \gamma \) are weighting parameters. \( \mu_X \) and \( \sigma_X \) denote the mean and standard deviation of \( X \), respectively. Similarly, \( \mu_{\hat{X}} \) and \( \sigma_{\hat{X}} \) denote the mean and standard deviation of \( \hat{X} \), respectively. \( \sigma_{X\hat{X}} \) is the covariance between \( \hat{X} \) and \( X \). \( C_1, C_2, \) and \( C_3 \) are constants. Further, Eq. (5) can be simplified when \( \alpha = \beta = \gamma = 1 \) and \( C_3 = C_2^2 \) as
\[
SSIM = \frac{(2\mu_X\mu_{\hat{X}} + C_1)(2\sigma_X\sigma_{\hat{X}} + C_2)}{(\mu_X^2 + \mu_{\hat{X}}^2 + C_1)(\sigma_X^2 + \sigma_{\hat{X}}^2 + C_2)}
\] (6)

In comparison, SSIM [135] is reported to reflect visual quality better than PSNR. Generally, PSNR and SSIM [135] are full-reference metrics that assess the quality of images based on natural scene statistics. SIM [136] is a full-reference metric that assesses the quality of the evaluated image.

3) IFC [136]: The information fidelity criterion (IFC) [136] is a full-reference metric that assesses the quality of images based on natural scene statistics. Research shows that the statistics of the space formed by natural images can be characterized using various models (e.g., the Gaussian scale mixtures). Generally, distortions would disturb the statistics of natural scenes and make images unnatural. According to these observations, Sheikh et al. [136] propose to measure the visual quality of an image via jointly using the natural scene and distortion models to quantify the mutual information between the test image and reference. Overall, the IFC [136] performs well for the quality assessment of super-resolved images [140].

4) LPIPS [137]: The learned perceptual image patch similarity (LPIPS) [137] is a learned metric for reference-based image quality assessment. More specifically, LPIPS [137] is obtained via computing the l2 distance between the reference and the test image in a deep feature space, which shows a good agreement with human judgments.

5) NIQE [138]: The natural image quality evaluator (NIQE) is a completely blind metric without the knowledge of human judgments or distortions [138]. The multivariate Gaussian (MVG) model is used to fit the “quality-aware” features extracted from images. More specifically, the features include the parameters of the generalized Gaussian distribution (GGD) and the asymmetric generalized Gaussian distribution (AGGD) that characterize the behavior of image patches. Then, the quality of an image is measured using the distance between the two MVG models fitting natural images and the evaluated image.

6) PIQE [139]: The perception-based quality evaluator (PIQE) is a no-reference image quality assessment metric [139]. Considering that the attention of human visual system
\[10\]The source code of IFC [136] is available at https://live.ece.utexas.edu/research/Quality/index_algorithms.htm.
\[11\]The source code of LPIPS [137] is available at https://github.com/nichzhang/PerceptualSimilarity.
\[12\]The source code of NIQE [138] is available at https://live.ece.utexas.edu/research/Quality/index_algorithms.htm.
\[13\]The implementation of PIQE [139] is included in Matlab as https://www.mathworks.com/help/images/ref/piqe.html.

(HVS) is highly directed towards spatially active regions, the test image is divided into non-overlapping blocks and block-level analysis is conducted to identify distortion and grade quality. Therefore, PIQE [139] can provide a spatial quality map. The overall quality of the evaluated image can be obtained by pooling the block level quality scores.

7) NRQM [116]: This is a learned no-reference quality metric (NRQM) for assessing super-resolved images [116]. To predict the perceptual scores of super-resolved images, three groups of statistical features including local frequency features, global frequency features, and spatial features are extracted. The selected features cover the distribution of discrete cosine transform coefficients, the distribution of wavelet coefficients, the spatial discontinuity property of pixel intensity, etc. On this basis, three regression forests are used to model these features independently and their results are combined linearly to estimate the final perceptual score. These three forests and the linear regression model are trained on a large-scale dataset of super-resolved images with perceptual scores. Overall, the visual quality predicted by NRQM [116] matches subjective evaluation well on SR results.

IV. TECHNOLOGIES AND METHODS

Researchers have been studying the SISR methods for practical applications. Especially with the SR performance on synthetic data becoming better and better, more and more attention has been paid to RSISR. Fig. 2 presents the overall taxonomy of existing RSISR techniques. Note that we focus more on deep learning-based methods. According to the primary principles and characteristics of existing RSISR methods, we group them into four categories, i.e., degradation modeling-based methods [88]–[98], image pairs-based methods [79]–[87], domain translation-based methods [99]–[100], and self-learning-based methods [94], [111]–[115]. Fig. 3 and Table III summarize existing RSISR methods. It is worth noting that one method may belong to different categories when it is viewed from different perspectives. The following sections introduce these methods in detail.

A. Degradation Modeling-based Methods

Compared with the SR of synthetic LR images, one of the main challenges for RSISR is that the degradation model (i.e., the \( D(\cdot) \) in Eq. (1)) is unknown. Generally, the degradation parameter set is necessary to design the objective function for reconstruction-based SISR methods derived from the...
Fig. 3. Milestones of RSISR methods.

Fig. 4. The general idea of degradation modeling-based methods.

Maximum a Posteriori (MAP) estimation. For learning-based methods that aim to obtain the mapping from LR images to their HR counterparts, the degradation parameter set is crucial for building training datasets. Therefore, as presented in Fig. 4, an intuitive way is to estimate the degradation parameter of the LR input prior to super-resolving or to iteratively optimize the degradation parameter and the super-resolved image. Eq. (3)

\[
\min_{X, b} \lambda \left\| SBX - Y \right\|^2_2 + \beta \left\| X - \hat{X} \right\|^2_2 + \eta \left\| RX, b \right\|
\]

where \(\lambda\) and \(\eta\) are parameters for balancing different terms. \(\hat{X}\) denotes the super-resolved image generated by a non-blind learning-based method, and \(b\) denotes the blur kernel corresponding to the blur matrix \(B\). \(\beta \) represents the direct bi-\(l_0\)-\(l_2\)-norm regularization term for the intermediate super-resolved image \(X\) and the blur kernel \(b\), which is beneficial to the accurate estimation of \(b\). After iteratively optimizing the \(X\) and \(b\) in Eq. 7, the estimated blur kernel \(\hat{b}\) can be combined with non-blind SR methods to produce an HR estimate. In [89], Shao et al. introduce the \(l_\alpha\)-norm-based adaptive heavy-tailed image prior to further improve the above approach. The studies in [88] and [89] demonstrate that, with the aid of effective constraints, the iterative optimization of the blur kernel and the super-resolved image is good for the accuracy of blur kernel estimation.

Different from the above numerical optimization-based approaches [88], [89], the blur kernel and the super-resolved image can also be jointly optimized using deep neural networks [90]–[92]. Generally, the mismatch of blur kernels would result in artifacts in the super-resolved image, e.g., over-smoothing or over-sharpening. Based on this observation, Gu et al. [90] and Cornillere et al. [91] propose to progressively correct the inaccurate kernel according to the quality of the super-resolved image. More specifically, they develop degradation-aware SR networks to produce HR images, in which the blur kernel is utilized as auxiliary information for SR. Meanwhile, corresponding deep neural networks are designed to correct the kernel with the guidance of the intermediate SR result. Unlike previous approaches [90], [91] that combine two or more networks, Huang et al. [92] develop a deep alternating network (DAN) for RSISR, in which the iterative optimization process between the super-resolved image and the blur kernel is unfolded to an end-to-end trainable network. DAN [92] consists of a chain of alternately stacked restorers and estimators, which are responsible for the restoration of the HR image and the estimation of the blur kernel, respectively. For the above methods, the super-resolved image and the blur kernel corresponding to the LR input are iteratively refined.

\[16\]

The source code of IKC [90] is available at https://github.com/yuanjunchai/IKC.

\[17\]

The source code of DAN [92] is available at https://github.com/greatlog/DAN.

\[15\]

In some cases, the noise is not explicitly characterized. Natural image priors are generally incorporated to suppress noise.
## TABLE III

**An overview of existing works on RSISR.**

| Methods           | Published | Category                   | Keywords                                                                 |
|-------------------|-----------|----------------------------|-------------------------------------------------------------------------|
| SupER             | TPAMI-2020| Image pairs-based          | Benchmarking super-resolution on real data                              |
| LP-KPN (RealSR)   | ICCV-2019 | Image pairs-based          | Laplacian pyramid-based kernel prediction network                       |
| CDC (DRealSR)     | ECCV-2020 | Image pairs-based          | Component divide-and-conquer model, Gradient weighted loss              |
| CameraSR (City100)| CVPR-2019 | Image pairs-based          | SR from the perspective of camera lenses                                |
| ZLLZ (SR-RAW)     | CVPR-2019 | Image pairs-based          | RAW sensor data, Contextual bilateral loss                              |
| TSRN (TextZoom)   | ECCV-2020 | Image pairs-based          | Sequential residual block, Central alignment module, Gradient profile loss|
| ImagePairs        | CVPRW-2020| Image pairs-based          | A new data acquisition technique for gathering real image data          |
| RawSR             | CVPR-2019 | Image pairs-based          | Two-branch structure, Raw image, Color correction                       |
| SARNBSR           | ICIG-2015 | Degradation modeling-based | Blur kernel estimation, Bi-L2-norm regularization                       |
| AHTNBSR           | JMIV-2019 | Degradation modeling-based | Adaptive heavy-tailed image priors, Nonparametric blur kernel estimation |
| IKC               | CVPR-2019 | Degradation modeling-based | Iterative kernel correction, Spatial feature transform                  |
| SVDBSR            | TOG-2019  | Degradation modeling-based | Degradation-aware SR network, Kernel discriminator network              |
| DAN               | NeurIPS-2020| Degradation modeling-based | SR image restorer, Blur kernel estimator, End-to-end trainable         |
| NBSR              | ICCV-2013 | Degradation modeling-based | Kernel estimation, Recurrence of small image patches                    |
| KernelGAN         | NeurIPS-2019| Degradation modeling-based | Deep internal learning, Cross-scale recurrence property, GAN, Image-specific SR-kernel |
| FISR              | ECCV-2018 | Degradation modeling-based | High-to-low GAN, Low-to-high GAN, Unpaired LR and HR images             |
| KMSR              | ICCV-2019 | Degradation modeling-based | Realistic blur kernels, Blur kernel pool augment, GAN                   |
| DML               | ACCV-2020 | Degradation modeling-based | Realistic HR-LR image pair synthesis, Pixel-wise spatially variant degradation kernel |
| RSRKN             | CVPRW-2020| Degradation modeling-based | Degradation framework, Kernel estimation, Noise injection, GAN           |
| CinCGAN           | CVPRW-2018| Domain translation-based   | Unsupervised learning, Cycle-in-cycle network structure, GAN            |
| MCinCGAN          | TIP-2020  | Domain translation-based   | Unsupervised learning, Multiple cycle-in-cycle network structure, GAN    |
| DDGAN             | CVPRW-2020| Domain translation-based   | Unsupervised learning, Unknown degradation, Cycle-in-cycle GAN, Domain discriminator |
| PSUSR             | CVPR-2020 | Domain translation-based   | Unpaired kernel/noise correction network, Pseudo-paired SR network, GAN |
| USISRResNet       | CVPRW-2020| Domain translation-based   | Unsupervised learning, GAN, Mean Opinion Score-based loss function      |
| DNSR              | arXiv-2018| Domain translation-based   | Unsupervised degradation learning, Bidirectional structural consistency, Bi-cycle network |
| GAN-CIRCLE        | TMI-2020  | Domain translation-based   | Computed tomography, CycleGAN                                           |
| DSGAN             | ICCVW-2019| Domain translation-based   | Frequency separation, Unsupervised learning, GAN                       |
| SRResCGAN         | CVPRW-2020| Domain translation-based   | Image observation model, Domain learning, GAN                           |
| RBSR              | WACV-2021 | Domain translation-based   | Bicubically down-sampled images, GAN                                    |
| ULSR              | ICCVW-2019| Domain translation-based   | Unsupervised learning, Unpaired data, GAN                              |
| ISPUSR            | CVPRW-2020| Domain translation-based   | Unsupervised image translation, Supervised SR, Collaborative training   |
| ZSSR              | CVPR-2018  | Self-learning-based       | Zero-shot, Internal recurrence, Deep internal learning, Image-specific CNN |
| DBPI              | SPL-2020   | Self-learning-based       | Unified internal learning, Downscaling/SR network, Dual back-projection loss |
| DualSR            | WACV-2021  | Self-learning-based       | Zero-shot, Dual-path architecture, GAN, Masked interpolation loss        |
| MZSR              | CVPR-2020  | Self-learning-based       | Meta-transfer learning, Large-scale training, External and internal information |
| MLSR              | ECCV-2020  | Self-learning-based       | Meta-learning, Patch-recurrence property                                |
joint optimization, the refined blur kernel and the super-
resolved image are supposed to be more accurate.

Previous studies have shown that natural image priors
such as patch recurrence property are useful for degradation
modeling. In [93], Michaeli et al. point out that the Point
Spread Function (PSF) is not the optimal blur kernel, and
they further propose to obtain the principled MAP estimate
of the blur kernel via maximizing the similarity of recurring
image patches across scales of the LR input.\footnote{The project homepage of NBSR [93] is at \url{http://www.wisdom.weizmann.ac.il/~vision/BlindSR.html}} The estimated
blur kernel can be used to degrade the LR input or natural
HR images artificially. In this way, the blur kernel estimation
approach is smoothly plugged into both self-example-based
and external-example-based SR approaches [47], [54]. The results in [92] show that the accuracy enhancement of blur
c kernel estimation leads to an obvious improvement of SR
performance on synthetic as well as real-world images.

Degradation modeling is also vitally important for deep
learning-based SR approaches. Deep convolutional neural
networks (CNN)-based SISR approaches usually achieve
state-of-the-art (SOTA) results on standard benchmarks.
Nevertheless, their performance is limited when applied
to real-world images. The main reason is that the kernel
(e.g., “bicubic” kernel) used to generate training data is
significantly different from the blur in a real scenario. To
address this problem, some recently presented deep learning-
based RSISR methods [94]–[98] adopt the pre-estimated
degradation parameters to generate samples for model training.
For example, inspired by [92], Bell-Kligler et al. [94] develop
an image-specific internal-GAN (i.e., KernelGAN) to learn
the internal distribution of patches.\footnote{The source code of KernelGAN [94] is available at \url{https://github.com/ssfkb/KernelGAN}} The KernelGAN
[94] is trained solely using the LR test image, making its
discriminator unable to differentiate the patch distribution
of the original LR input from that of the degraded version of
the LR image produced by the generator. After the joint training
with the discriminator, the generator can well characterize
the degradation process with an image-specific kernel. Then,
the LR test image and its degraded version generated by the
generator form paired data for SR model training. Bulat et al.
[95] train a generative adversarial network (GAN)-based
degradation model from unpaired HR and LR face images,
and then use the learned network to generate image pairs for
SR network training.\footnote{The source code of FISR [95] is available at \url{https://github.com/jingyang2017/Face-and-Image-super-resolution}} Zhou et al. [96] propose to obtain
a group of realistic blur kernels from real-world photographs
and a GAN is trained on them to augment the pool of realistic
blur kernels.\footnote{The source code of KMSR [96] is available at \url{https://github.com/IVRL/Kernel-Modeling-Super-Resolution}} With the augmented kernel pool, more realistic
and diverse LR-HR image pairs can be constructed to train
the SR model. Analogously, Xiao et al. [97] model spatially
variant degradation via learning a set of basis blur kernels
and corresponding pixel-wise weights from real-world image
pairs. The learned realistic degradation model is then used to
generate pseudo-realistic LR-HR image pairs. More recently,

\begin{itemize}
  \item Ji et al. [98] take this idea one step further and develop
an effective degradation framework using various realistic
blur kernels and noise distributions, winning the NTIRE 2020
Challenge on Real-World Image Super-Resolution [122].\footnote{The source code of RSRKN [98] is available at \url{https://github.com/jixiaozhong/RealSR}}
The outstanding performance of degradation modeling-based
RSISR methods demonstrates that degradation modeling is
meaningful and this kind of approach is a feasible solution
to the SR of real-world images.
\end{itemize}

\subsection{B. Image Pairs-based Methods}

Although paired LR-HR training data can be synthesized
from high-quality images according to pre-defined degradation
models [96], [98], deriving explicit realistic degradation models from real-world images is challenging. To deal with
this problem, researchers [79]–[85] propose to directly collect
the images of the same scene with different resolutions, which
are used to construct realistic LR-HR image pairs for RSISR
model training. Overall, as illustrated in Fig. 5 currently there are three main ways to collect real-world images for dataset
building, including the focal length adjusting-based approach
[80]–[84], the hardware binning-based approach [79], and the
beam splitter-based approach [85]. The representative realistic
datasets built with the above image collection approaches are
described in Section \ref{III-A}. Therefore, this section focuses on
the RSISR models developed on these real-world datasets.

Intuitively, given LR-HR image pairs, nearly all existing
supervised SR methods (e.g., SRCNN [67], VDSR [68], EDSR
[70], RDN [74], SRGAN [69], etc.) can be adopted to learn
the mapping from LR images to their HR counterparts. The
mapping learned from realistic datasets is supposed to apply
to the SR of real-world images. However, in fact challenges
remain.

For instance, the degradation kernels of real-world images
are generally non-uniform, varying with the depth in a real
scene. Thus, training an SR model that treats all pixels the same way as most previous deep CNN-based
SR approaches may not be the optimal solution. For this
problem, Cai et al. [80] propose the LP-KPN, which combines
the Laplacian pyramid with the pixel-wise kernel prediction
network (KPN), achieving good SR performance and high
efficiency.\footnote{The source code of LP-KPN [80] is available at \url{https://github.com/csjcai/RealSR}} Another challenge that cannot be ignored is the misalignment between LR and HR image pairs in the collected
realistic datasets. Although image registration is performed

\begin{figure}[h]
\centering
\includegraphics[width=0.8\textwidth]{fig5.png}
\caption{Existing solutions to construct realistic LR-HR image pairs.}
\end{figure}
to align realistic image pairs, misalignment is unavoidable. As a consequence of misalignment, blurring artifacts may be introduced in the reconstructed HR images when using these datasets to train the SR model with pixel-to-pixel losses (e.g., $l_1$ and $l_2$). Inspired by the Contextual Loss [142] and the edge-preserving bilateral filter [143], Zhang et al. [83] propose the Contextual Bilateral loss (CoBi) to resolve this issue. CoBi integrates the pixel-level information and spatial pixel coordinates to measure image similarity. Moreover, two spaces including RGB image patches and pre-trained perceptual-features (e.g., VGG-19 [144]) are jointly considered in CoBi to improve performance further. It is demonstrated that CoBi is robust to the mild misalignment in the realistic image pairs for supervised SR model training. Considering that pixel-wise losses are generally more focused on smoothing flat regions and sharpening edges while neglecting the recovery of realistic details of textures to some extent, Wei et al. [81] develop a Component Divide-and-Conquer (CDC) SR model for real-world images. More specifically, the flat, edge, and corner components are first predicted by three component-attentive blocks respectively in CDC and then they are aggregated to produce the final SR image based on the learned component-attentive maps. To achieve this goal, a gradient-weighted loss that can adapt the model training to the reconstruction difficulties of different image components is applied. The results on RealSR [80] and DRealSR [81] prove the superiority and generalization capability of CDC [81]. Given a dataset containing raw and color images, learning a mapping from LR raw images to HR color images using deep neural networks is an intuitive approach to exploit raw images for SR. However, one raw image could correspond to a set of color images because it does not have the information for the processes (e.g., color correction) within the image signal processing system, making the above naive way do not work well. To address this problem, Xu et al. [86], [87] design a two-branch CNN which jointly exploits the LR raw data and corresponding LR color image to recover fine structures and high-fidelity color appearances.

In addition to the above challenges shared by almost all real-world images, the SR of certain kinds of images (e.g., text images, remote sensing images, and medical images) usually has a particularity. Therefore, specific SR models should be designed for these scenarios. For example, the TSRN developed by Wang et al. [84] is an SR network for real scene text images. To leverage the strong sequential characteristics of text images, the Bi-directional LSTM (BLSTM) mechanism is added to basic residual blocks. In order to address the misalignment problem in the realistic text image dataset TextZoom, TSRN [84] introduces a spatial transform network-based central alignment module in the front of the network. Furthermore, aiming at enhancing the shape boundary of characters, a gradient prior loss is combined with the $l_2$ loss to train TSRN. It is demonstrated that the SR of real-world text images using TSRN does increase the recognition accuracy. Predictably, in some cases, SR can also benefit other computer vision tasks, e.g., objection detection [5] and semantic segmentation [4].

C. Domain Translation-based Methods

As introduced in Sections III-A and V-B, it is hard to obtain real-world datasets with well-aligned LR-HR image pairs. More often than not, what we have are only LR images for model training in practical applications. Or better yet, a set of HR images are available for reference besides LR training images, but there is no one-to-one correspondence between LR and HR images. The supervised approaches no longer apply in these cases due to the lack of paired samples. Previous studies [99]–[107], [107]–[110] demonstrate that domain translation is a feasible solution to deal with this problem. For this kind of RSISR approach, real-world LR images, synthetic LR images (also known as clean LR images or ideal LR images), and HR images are thought to be in different domains. Consequently, the SR of real-world images converts to the translation from the real-world LR image domain (RLRD) to the HR image domain (HRD). Overall, as presented in Fig. 6, there are two main ways to cross RLRD to HRD, i.e., the two-stage and the one-stage approaches, and the most notable difference lies in whether the synthetic LR image domain (SLRD) is used as a relay station.

Most existing SISR approaches are trained using synthetic data, thereby achieving excellent performance on clean LR images. As is known to all, there is a noticeable domain gap between SLRD and RLRD, causing the degradation of SR accuracy on real-world images. Intuitively, one can mitigate this performance degradation via reducing the domain gap, which is how the two-stage domain translation-based RSISR approaches work. As shown in Fig. 6, the two-stage approaches generally include two main steps, i.e., domain translation and SR. Usually, generic SR methods are adopted in the SR reconstruction phase, so as to benefit from pre-trained SR models learned from large-scale datasets. The Cycle-in-Cycle GAN (CinCGAN) developed by Yuan et al. [99] is a representative of this kind of RSISR method. More specifically, CinCGAN [99] first uses a domain translation network to map realistic LR images in RLRD into the SLRD, and then a pre-trained deep SR network with the ideal
degradation assumption is stacked to upscale the translation result to the desired size. Finally, the domain translation and SR networks are end-to-end fine-tuned. Inspired by CycleGAN [145], the domain translation network in CInCGAN [99] is trained to map realistic LR inputs to synthetic LR images (i.e., “bicubic”-downsampled images) using unpaired training data, which usually can suppress the artifacts such as noise in real-world LR images to make them more suitable for the following SR network. Results show that the CInCGAN [99] trained with unpaired data achieves comparable SR performance as supervised methods. In MCInCGAN [100], the CInCGAN [99] is improved via introducing a progressive multi-cycle framework for large-scale upsampling and a new constraint to suppress the color fluctuation in training. For more stable model training and better SR performance, the DDGAN developed by Kim et al. [101] further combines the pixel-wise loss, the VGG feature loss, and the SSIM loss to measure similarity. Meanwhile, a domain discriminator that takes the noise, texture, and color into consideration simultaneously is proposed to make the generated image more consistent with the target domain distribution. More recently, Maeda et al. [102] propose an end-to-end trainable framework UISRPS to jointly optimize the domain translation network and the SR network, achieving excellent SR results on real-world face images and aerial images. Benefiting the architecture, it is convenient to integrate existing SR networks and pixel-wise loss functions into UISRPS [102].

Different from the two-stage methods mentioned above, the one-stage domain translation-based RSISR frameworks aim to produce a super-resolved image directly from the real-world LR input, as presented in Fig. 6. How to learn the translation mapping from RLRD to HRD without real LR-HR image pairs is the crucial issue. Prajapati et al. [103] propose to train a GAN-based network USISRNNet to upsample real-world images. Since only unpaired LR and HR training images are available, USISRNNet is optimized through unsupervised learning. Beyond the standard GAN losses, a pixel-wise content loss, a Total-Variation loss, and a quality assessment loss are combined to optimize USISRNNet. The content loss makes the SR result be not far from the bicubically upsampled version, thus preserving the primary content of the LR image. The Total-Variation loss is integrated to suppress the noise and artifacts. For better perceptual quality of the super-resolved image, the learned Mean Opinion Score is used to construct the quality assessment loss. Thanks to the combination of multiple losses, USISRNNet [103] achieves good generalization capacity. Inspired by CycleGAN [145], some researchers propose to learn the direct relationship between RLRD to HRD using cycle consistency-constrained GANs [104], [105]. Given an LR image, the LR-to-HR generator (i.e., RLRD to HRD) is trained to reconstruct a vivid HR image that can be returned to the LR input by the corresponding HR-to-LR generator (i.e., HRD to RLRD). Conversely, an HR image should be well recovered by the LR-to-HR generator from its downsampled version produced by the HR-to-LR generator. After the joint training of the two generators and corresponding discriminators, the LR-to-HR generator models the direct mapping from RLRD to HRD and it is used to reconstruct HR images from realistic LR images.

Considering that learning the end-to-end translation between RLRD to HRD from unpaired LR-HR data is challenging, part of the one-stage domain translation-based RSISR methods [106]–[110] also use the synthetic LR image as a bridge in the training phase. Given unpaired realistic LR and HR images, Fritsche et al. [106] first bicubically downsample HR images. Bicubically downsampled results are then translated into the realistic domain to make them follow real scene characteristics, using a standard GAN-based domain translation network trained on the bicubically downsampled images and realistic LR images in an unsupervised fashion. Taking the pseudo-realistic LR images and corresponding HR images as training sample pairs, the ESRGAN [146] is trained for upsampling in a supervised manner. In order to generate images well matching the target distribution, both domain translation and SR networks are optimized with frequency separation-based loss functions. [31] More specifically, the color loss, the texture loss, and the perceptual loss are employed to the low-frequency component, the high-frequency component, and the whole image, respectively. Note that only the SR model is needed to upscale real-world images in the testing phase because it is trained on the image pairs that follow real-world image distribution. On this basis, recently Umer et al. [107] improve the GAN-based SR model following the real-world image observation model, thus exploiting the powerful regularization and optimization techniques simultaneously. Rad et al. [108] convert realistic LR images to bicubic look-alike images based on their copying mechanism and bicubic perceptual loss. Different from the above works [106]–[108] which use a single direction domain translation model, Lugmayr et al. [109] and Chen et al. [110] propose to train a bi-directional domain translation model with the cycle consistency constraints for better robustness.

Overall, domain translation is an effective way to reduce the domain gap between synthetic and realistic data, thus improving the generalization capability of SR models on ever-changing real-world images. In contrast, the two-stage domain translation-based RSISR approaches can integrate synthetic data-trained SR models more elegantly, while the one-stage methods generally have lower complexity in the testing phase.

D. Self-Learning-based Methods

Most existing RSISR methods use external dataset (i.e., paired or unpaired training data) to train SR models. Therefore, the SR performance is tightly bound to the consistency between testing data and training data. However, real-world

[27] The source code of DDGAN [101] is available at https://github.com/GT-KIM/unsupervised-super-resolution-domain-discriminator.

[28] The source code of USISRNNet [103] is available at https://github.com/kalpesh89/USISRNNet.

[29] The source code of GAN-CIRCLE [105] is available at https://github.com/charlesyou999648/GAN-CIRCLE.

[30] The source code of DSGAN [106] is available at https://github.com/ManuelFritsche/real-world-sr.

[31] The source code of SRRResGAN [107] is available at https://github.com/RaoUmer/SRRResGAN.
images do not always obey the characteristics of training data. In order to reduce the impact of the training–testing discrepancy on SR performance, researchers propose to exploit the internal information of the LR input to learn image-specific SR model as shown in Fig. 7.

The “Zero-Shot” SR (ZSSR) developed by Shocher et al. [111] is one of the representatives. The self-supervised approach ZSSR [111] is based on the cross-scale internal recurrence of information, which is a common property of natural images. More specifically, an eight-layer CNN is trained to model image-specific LR-HR relations in the testing phase, using the example pairs extracted from the LR test image and its degraded version. In consideration of the insufficiency of training data (the test image only), data augmentation is adopted when extracting image-specific LR-HR pairs. Since ZSSR [111] can adapt itself to different testing images, it achieves excellent SR performance on real-world images, whose degradation process is non-ideal and unknown. Again based on the cross-scale recurrence property, Bell-Kligler et al. [94] propose to train an image-specific GAN (KernelGAN) to model the degradation process (i.e., the blur kernel) of the input. Therefore, a fully self-supervised image-specific RSISR framework can be achieved when the blur kernel estimation module KernelGAN [94] is plugged into the reconstruction module ZSSR [111]. To jointly train the image-specific degradation and SR networks, Kim et al. [112] design a unified internal learning-based SR framework DBPI, consisting of an SR network and a downsampling network. In the self-supervised training phase of DBPI, the SR network is optimized to reconstruct the LR input image from the its downscaled version produced by the downsampling network. Meanwhile, the downsampling network is trained to recover the LR input image from its super-resolved version generated by the SR network. Similarly, Emad et al. [113] propose the DualSR that jointly optimizes an image-specific downsampler and corresponding upsampler. More specifically, DualSR [113] is trained with the cycle-consistency loss, the masked interpolation loss, and the adversarial loss using the patches from the test image. Results in [112], [113] show that the complementary training of the image-specific degradation and SR networks is beneficial to the reconstruction performance.

Although self-learning-based RSISR approaches such as ZSSR [111], KernelGAN [94], and DBPI [112] can be easily adapted to LR input images, they generally have two main shortcomings due to the self-supervised training strategy. First, the optimization of SR models only utilizes the internal information of the LR input, while a great deal of external information is neglected. Second, these methods are usually time-consuming in the testing phase because of online training. To overcome these disadvantages, meta-learning is introduced into recent self-learning-based SR methods [114], [115]. Based on ZSSR [111], Soh et al. [114] present the meta-transfer learning for zero-shot SR (MZSR), which consists of three steps, i.e., large-scale training, meta-transfer learning, and meta-test. In order to ease the training of the SR network and the meta-learning, the large-scale training step first trains an eight-layer SR network with the pixel-wise $l_1$ loss on the large-scale dataset DIV2K [128]. The meta-transfer learning process aims to find a generic initial point for internal learning following the Model-Agnostic Meta-Learning [147], making the model can be quickly adapted to new image conditions within a few gradient updates. In the meta-test phase, the input test image is first degraded to produce example pairs for model parameter update, and then it is fed into the updated model to generate an SR result. Thanks to the meta-transfer learning strategy, MZSR [114] achieves competitive performance in terms of both the quality of the super-resolved image and the running time. In [115], Park et al. also propose to improve the performance of SOTA SR networks such as RCAN [73] using the meta-learning strategy, without changing the original architectures. On the whole, meta-learning-based SR approaches have strengths in reconstruction quality, generalization capability, and processing efficiency.

V. Comparisons among State-of-the-Arts

In this section, we compare representative RSISR methods on benchmark datasets. More specifically, the selected competitors are ZSSR [111], KernelGAN [94], MZSR [114], DBPI [112], DAN [92], IKC [90], and SRResCGAN [107], covering multiple kinds of approaches mentioned in Section IV. For these SR approaches, we use the official models provided by authors in the comparison, and the upsampling factor is set to 2 or 4. Two benchmark datasets are tested, including the DIV2KRK [94] and RealSR [80]. As introduced in Section III-A, DIV2KRK [94] is a synthetic dataset with random kernels and RealSR [80] is a realistic dataset collected by adjusting the focal length. In addition to the subjective quality comparison presented in Figs. 8-11, the SR results by different methods are objectively evaluated in Table LV on full-reference and no-reference image quality assessment metrics, including PSNR, SSIM [135], IFC [136], LPIPS [137], NIQE [138], PIQE [139], and NRQM [116]. Beyond reconstruction accuracy, the model size and execution speed are also significant for SR algorithms. Therefore, the number of parameters and running time are also presented in Fig. 12.
Fig. 8. Super-resolution results comparison (×2) on the image taken from DIV2KRK [94].

Fig. 9. Super-resolution results comparison (×4) on the image taken from DIV2KRK [94].

Fig. 10. Super-resolution results comparison (×2) on the image taken from RealSR [80].
Fig. 11. Super-resolution results comparison (×4) on the image taken from RealSR [80].

Fig. 12. The number of parameters and the average running time on the images taken from RealSR [80].

It is worth noting that the results shown in this section may be different from those in the original paper due to different settings of test environments, hyper-parameters, etc. The aim of these comparisons is not to find a winner in terms of accuracy or efficiency, but to indicate the current state of the research on RSISR. In fact, as is known to all, it is not easy to make a completely fair comparison among these competitors due to the complexity of settings. As far as we know, in particular, there is no uniform or universally accepted settings yet for the comparison of RSISR models.

We can make the following observations from the comparison results on visual quality, objective quality, and complexity. (i) Compared with conventional interpolation (e.g., “Bicubic”), SR is undoubtedly a more effective way to obtain HR images. (ii) Overall, there is an obvious gap between the super-resolved image and the corresponding ground-truth in terms of visual effects, especially for texture and edge regions. For example, some SR results suffer from over-smoothing or over-sharpening artifacts. (iii) There are some differences between subjective and objective assessment results. Moreover, the scores by different objective assessment metrics may not be necessarily consistent with each other. (iv) In general, self-supervised learning-based SR approaches have fewer parameters than the SR models trained on large-scale datasets, but take longer to produce upsampled images.

VI. CURRENT CHALLENGES AND FUTURE DIRECTIONS

The numerous studies reviewed in Sections III and IV demonstrate the great progress of the research on RSISR. In fact, however, there are still problems requiring further exploration. We discuss some of the challenges and promising directions for RSISR in this section.

A. Image Datasets

Overall, the data for SR model training may be equally as crucial as the SR techniques for the study on RSISR, especially for deep learning-based solutions. Several realistic datasets have been constructed in the past few years, significantly boosting the reconstruction performance. However, compared with the datasets for popular computer vision tasks such as classification and detection, the lack of realistic datasets for RSISR is still striking. Therefore, it is desired to build larger and more representative/targeted realistic datasets for RSISR with considering the limiting factors of imaging resolution in the future. Meanwhile, more accurate alignment of the images captured from the same scene with different resolutions is also needed.

B. SR Algorithms

Although the SR performance on real-world images is getting better and better, there is still a long way to go before applying RSISR algorithms to practical applications. First, the LR images captured in real scenarios are likely to suffer from
Third, it is hard to obtain paired training data, even unpaired data or relevant HR references in some cases. Thus it is promising to develop RSISR models that can run with unpaired training data or even the LR input only. Moreover, how to leverage fewer models to meet personalized and multifunctional demands (e.g., the need for arbitrary upscaling factors and the preference to perceptual quality) of users deserves further investigation.

### C. Evaluation Criteria

The evaluation criteria are vitally crucial for the research on computer vision tasks. On the one hand, the design of objective functions is generally guided by the evaluation criteria. For example, the $l_2$ loss is prevalent for image/video restoration tasks because it is highly correlated to the commonly used quality assessment metric PSNR. On the other hand, evaluation criteria are needed to make comparisons among different approaches, thus continuously advancing techniques. As previously mentioned, currently the PSNR and SSIM are the two of the most popular evaluation metrics for SR. However, previous studies show that they are unable to measure the visual quality of super-resolved images accurately. In addition, PSNR and SSIM are full-reference evaluation metrics that cannot be adopted in practical applications.

### Table IV

The performance of representative RSISR algorithms on DIV2KRK [94] and RealSR [80] datasets.

| Method       | Scale | PSNR ↑ (dB) | SSIM ↑ | IFC ↑ | NIQE ↓ | PIQE ↓ | NRQM ↑ | LPIPS ↓ |
|--------------|-------|-------------|--------|-------|--------|--------|--------|--------|
| Bicubic      | x2    | 27.24       | 0.7846 |       |        |        |        |        |
|              | x4    | 23.89       | 0.6478 | 3.022 | 5.196  | 79.90  | 3.273  | 0.3631 |
| ZSSR [111]   | x2    | 27.51       | 0.7925 | 3.000 | 5.068  | 80.06  | 3.435  | 0.3477 |
|              | x4    | 24.05       | 0.6550 | 1.132 | 5.824  | 90.29  | 3.109  | 0.5257 |
| KernelGAN [94] | x2    | 28.84       | 0.8379 | 3.720 | 5.099  | 72.17  | 3.920  | 0.2929 |
|              | x4    | 24.76       | 0.6799 | 1.245 | 5.886  | 88.72  | 3.610  | 0.4980 |
| MZSR (1) [114] | x2    | 26.69       | 0.7889 | 2.515 | 5.627  | 35.97  | 4.112  | 0.2630 |
|              | x4    | 29.55       | 0.8657 | 4.084 | 5.239  | 50.61  | 4.844  | 0.2641 |
| DBPI [112]   | x2    | 31.06       | 0.8848 | 5.076 | 4.041  | 56.14  | 3.519  | 0.1667 |
|              | x4    | 24.92       | 0.7035 | 1.385 | 5.163  | 70.74  | 4.980  | 0.4039 |
| DAN [92]     | x2    | 25.41       | 0.7255 | 1.691 | 5.140  | 79.72  | 3.869  | 0.3977 |
|              | x4    | 26.15       | 0.7486 | 1.808 | 3.717  | 35.88  | 4.976  | 0.2463 |
| SRResCGAN [107] | x2    | 24.00       | 0.6497 | 1.024 | 5.038  | 74.27  | 3.054  | 0.5054 |

Performance on the real-world dataset RealSR [80]

| Method       | Scale | PSNR ↑ (dB) | SSIM ↑ | IFC ↑ | NIQE ↓ | PIQE ↓ | NRQM ↑ | LPIPS ↓ |
|--------------|-------|-------------|--------|-------|--------|--------|--------|--------|
| Bicubic      | x2    | 30.27       | 0.8736 | 1.921 | 5.569  | 83.90  | 2.731  | 0.2095 |
|              | x4    | 25.74       | 0.7413 | 0.890 | 6.228  | 92.53  | 2.802  | 0.4666 |
| ZSSR [111]   | x2    | 30.56       | 0.8786 | 1.949 | 5.376  | 81.09  | 2.749  | 0.1756 |
|              | x4    | 25.83       | 0.7434 | 0.897 | 4.971  | 83.01  | 2.797  | 0.3503 |
| KernelGAN [94] | x2    | 30.24       | 0.8907 | 2.106 | 5.384  | 77.10  | 2.769  | 0.1338 |
|              | x4    | 24.09       | 0.7243 | 0.897 | 4.918  | 78.96  | 3.559  | 0.2981 |
| MZSR (1) [114] | x2    | 27.96       | 0.8160 | 1.520 | 5.887  | 38.83  | 2.868  | 0.2105 |
|              | x4    | 27.86       | 0.8285 | 1.876 | 5.698  | 54.87  | 2.995  | 0.1777 |
| DBPI [112]   | x2    | 22.36       | 0.6562 | 0.851 | 5.640  | 70.58  | 5.056  | 0.3106 |
|              | x4    | 30.63       | 0.8815 | 1.959 | 4.387  | 68.68  | 2.745  | 0.1314 |
| DAN [92]     | x2    | 26.20       | 0.7598 | 0.966 | 6.096  | 90.57  | 2.834  | 0.4095 |
|              | x4    | 25.60       | 0.7488 | 0.944 | 4.845  | 82.75  | 2.927  | 0.3188 |
| IKC [90]     | x2    | 26.26       | 0.7983 | 1.573 | 3.786  | 39.40  | 4.129  | 0.2090 |
|              | x4    | 25.84       | 0.7459 | 0.900 | 5.009  | 74.45  | 2.795  | 0.3746 |

Distinctly different degradations, challenging existing RSISR algorithms. Therefore, it is necessary to make RSISR models can adapt themselves to ever-changing real-world images. Second, most existing RSISR approaches are with a large model (e.g., a deep network), thereby requiring vast computing resources/time for forward inference and plenty of space for parameters storage. However, these resources are generally limited in real-world applications. Hence, how to achieve lightweight design and implementation of SR models without significant performance degradation is a primary challenge. Third, it is hard to obtain paired training data, even unpaired data or relevant HR references in some cases. Thus it is promising to develop RSISR models that can be run with unpaired training data or even the LR input only. Moreover, how to leverage fewer models to meet personalized and multifunctional demands (e.g., the need for arbitrary upscaling factors and the preference to perceptual quality) of users deserves further investigation.
Therefore, developing more suitable evaluation criteria for RSISR is a crucial and urgent research problem. On the whole, task-specific evaluation metrics are needed. That is, we have to take the goals and characteristics of RSISR into consideration while developing evaluation criteria. For example, the common targets include smoothness preserving for flat areas, detail enhancing for textures, sharpening for example, the common targets include smoothness preserving into consideration while developing evaluation criteria. For RSISR is a crucial and urgent research problem. On the great demands.

quality assessment criteria for super-resolved images have remains a challenge. Furthermore, there are no HR images for reference in practical applications. Thus the no-reference quality assessment criteria for super-resolved images have great demands.

VII. CONCLUSION

In recent years the super-resolution of real-world images has been getting increased attention. This paper briefly reviews recent super-resolution methods for realistic images, including degradation modeling-based algorithms, image pairs-based algorithms, domain translation-based algorithms, and self-learning-based algorithms. Meanwhile, we summarize the commonly used datasets and assessment metrics for RSISR models training and evaluation. Moreover, although some progress has been made on RSISR in the past few years, we point out that there are still challenges to be further addressed, e.g., realistic datasets for model training and testing, specific models for real-world image super-resolution and reconstruction performance evaluation. These unsolved problems also indicate the promising directions for future exploration. We expect that this review can give a better understanding of existing studies for researchers, and also hope that it can attract more attention to advance the progress and application of real-world image super-resolution techniques.

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