http://www.jctjournals.com ISSN(ONLINE):2278 – 3814

Volume-11, Issue-02, February, 2022
JOURNAL OF COMPUTING TECHNOLOGIES (JCT)
International Journal
Page Number: 01-06

A Literature Survey on Single Image Super Resolution Using Different Algorithm

Devidas Sopanrao Sonwane [1], Prof. Jayanand Ambadas kamble [2]
M.Tech Student[1], Assistant Professor[2],
[1,2]Department of Computer Science and Engineering
[1,2]Maratha Institute of Technology (MIT), Aurangabad, (M.H.), INDIA
[1]dssonwane2016@gmail.com, [2]jayanand.kamble@mit.asia

***Abstract*— In this survey discuss the super image resolution using different methods. In mainly focus on the researches of recent years and classify them into non-deep learning SR algorithms and deep learning SR algorithms. The shortcomings in commonly used kernel-based super-resolution drive the study of improved super-resolution algorithms of higher quality. In the past years a wide range of very different approaches has been taken to improve super-resolution. In the last decade there are different methods are presented in this research area.The paper presents a survey of recent single image super resolution methods that are based on the use of external database to predict the values of missing pixels in high resolution image In this research work discuss these methods and also compare the different results on the basis of these parameter.**

Keywords - Single Image Super Resolution (SISR), Low-Resolution (LR), Artificial Intelligence (AI), Two-Stage Network (TSN), Soft Gradient Clipping (SGC), Transformer Network for Image Super-Resolution (TTSR) etc…

I. INTRODUCTION

In past few decades, single image super-resolution (SISR) that seeks for recover a large (HR) photograph from a low-resolution (LR) measurement, has become a popular issue in the field of image analysis. For recognition systems, single-image super-resolution is necessary, as well as several technologies have been implemented in recent decades. Due to their perceived achievement, these solutions seem to be frequently dependent on several of factors, as well as unique datasets and measurements. The procedure of creating high-resolution photos from low-resolution photos is called as super-resolution (SR). To put it another way, LR refers to the single picture input, HR to the real statistics, and SR to the anticipated high resolution. High-resolution images have more pixel density than low-resolution images. With this feature, high-resolution images are desired for much real-life application because HR images provide more detail and information about the scene [2]. The object using single image super- resolution (SISR) is just to reconstruct the high-resolution frame from with a low-resolution frame inside this case. When high-frequency picture information is generally being extracted from such a low-resolution visual, SISR becomes hard. The brightness of large pictures is reduced absent increased signals. SISR is indeed a poorly challenge even though a single low- resolution photo may generate in multiple high-resolution representations [3].

Deep Learning

Deep learning is an artificial intelligence (AI) activity essentially simulates human mind's analysis input information as well as structure formulation through order to make a decision. Usually it is called as the deep learning model or deep convolution neural network. Deep learning, also every linear response to convert the incoming data it into increasingly abstract as well as model is an appropriate. The information inside a computer vision implementation can be a structure of images; a first truly representative layer might subjective the pixel density as well as convert seams; the middle level can really build or transmit side accommodations; the core layer can generate an eyes and mouth; and its fourth layer could represent however that image proposed recognition [4].

Significantly, Neural network is a type of learning algorithms primarily teaches the machine understand common sense. In machine learning, a software program comes to understand a function trained data set on difficult and complicated information in the form of pics, word, or noise [1].

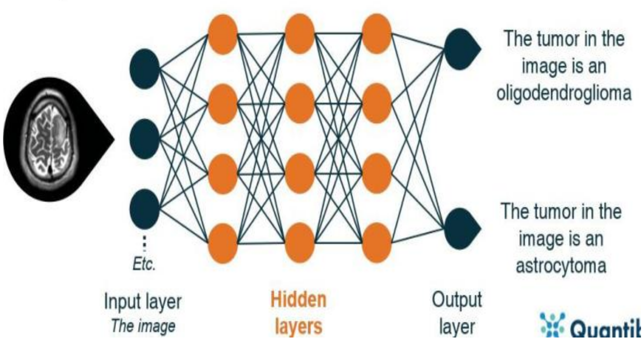

Fig. 1. Deep Learning [3]

In the next section discuss the previous works that is presented by different researchers after that discuss the technical background for multiple image super resolution in section III describe Section IV discusses the result parameters of the proposed method. Last but not least discuss the conclusion in section V.

II LITERATURE SURVEY

Yuzhuo Han et.al. (2021), In this research work presented a two-stage network (TSN).The one stage is learning how to transform LR images into LR images with high-frequency information. The other stage is learning how to transform LR images with high frequency information into HR images. Meanwhile, author presented a two-stage learning loss, network jointly learning how to transform LR images into LR images with high-frequency information and transform LR images with high-frequency information into HR images. Extensive experiments show TSN can reconstruct the clear super-resolution images with fewer parameters [25].

Younghyun Jo et.a.(2021) In this research work presented a simple and practical single-image SR method by using LUT (SR-LUT). Method is inherently faster as pre-computed HR values are just retrieved from the SR-LUT and a few calculations are conducted for the final output. Compared to bicubic interpolation, fast models run faster while achieving better quantitative performance by a good margin, and slow model shows the better visual quality with a little more runtime. Authors preferred in practical usages due to its speed and ease of implementation [24].

Chunmeng Wang_ et.al, (2021) In this research work presented“Fast image super- resolution with the simplified residual network” for image super- resolution. Two-level residual network includes external residual level and internal residual level to learn more effective high-frequency information. They first introduce a Laplacian layer to process the input LR image with the Laplacian filter, which makes the input value closer to the residual value to speed up the training, and introduce the efficient channel-average layer instead of using the convolution filters.This method, known as "soft gradient clipping" (SGC), has been shown by researchers to provide rapid training speeds. The researcher's technique considerably increases training and building efficiency over the prior residual networks. This technique has been evaluated using publicly available datasets, and the results demonstrate that it delivers real-time UHD video playback with acceptable visual quality [23].

Zhang, K., et.al (2020), In this research work presented researcher focus on the classical SISR degradation model and present a deep unfolding super-resolution network. Researchers built their design on the standard model-based method's unfolding optimization to create an end-to-end trainable deep network of model based methods and the advantages of learning-based methods. Using a single model, the suggested network is able to handle both the traditional degradation model and the unique degradation model provided by the researchers. Specifically, the proposed network consists of three inter preventable modules, including the data module that makes HR estimation clearer, the prior module that makes Cleaning up the HR estimation process and the hyper-parameter module that manages the other two modules' outputs. As a result, the presented method can impose both degradation constrain and prior constrain on the solution. Extensive experimental results demonstrated the flexibility, effectiveness and generalization of the presented method for super-resolving various degraded LR images. researchers believe that our work can benefit to image restoration research community [20].

Li, K., et.al. (2020), In this research work presented effort in the area of picture super resolution reconstruction. To begin, various picture super-resolution reconstruction task assessment indices, PSNR, SSIM, PI, and RMSE, are presented. Then, according to the model based categories, the interpolation-based, regularization based, CNN-based and GAN-based models are introduced, respectively. New interpolation methods and filters are based on the SISR model of the interpolation technique, which is a foundation for both of these new classic models. The method of regularization is mainly introduced by introducing two models that add a regularization loss function, and then experimentally observe the texture and details generated by the method. In the CNN-related models, since the birth of the SRCNN, the depth of the CNN has become larger and larger with the introduction of the ResNet network. In recent years, researchers have pursued better performance while taking into account the complexity of structures and algorithms, and a lightweight network model presented. Because the reconstructed picture will be excessively smooth and lack detail, GAN-based models do not aim for a higher PSNR than CNN-based models. Therefore, it is presented to apply the perceived loss to the network to make the constructed image have excellent texture and detail. However, the original model is prone to distortion and accompanied by artifact [19].

Yang, F.,et.al (2020), In this research work presented a novel Texture Transformer Network for Image Super-Resolution (TTSR) which transfers HR textures from the Ref to LR image. The presented texture transformer consists of a learnable texture extractor which learns a jointly feature embedding for further attention computation and two attention based modules which transfer HR textures from the Ref image.In addition, the texture converter and CSFI module given here may be used in a cross-scale manner to create a more powerful feature representation. In both quantitative and qualitative assessments, this TTSR outperforms current better result, as shown by extensive testing [17].

Table I. Comparison of Different Previous Methods

S.NO	REF.	YEAR	TOPIC	METHODS
1	[25]	2021	Two-stage Network For Single Image Super- Resolution	Single-Image Super- Resolution (SISR), Convolutional Neural Networks CNN-Based
2	[24]	2021	Practical Single-Image Super-Resolution Using Look-Up Table	Super Resolution(SR) Method, DNN Based Methods
3	[23]	2021	Fast image super-resolution with the simplified residual network	Super- Resolution(SR) Convolutional Neural Network(CNN),Single-Image Super-Resolution (SISR)
4	[20]	2020	Deep Unfolding Network for Image Super-Resolution	MAP (maximum a posteriori)
5	[19]	2020	A Survey of Single Image Super Resolution Reconstruction	Super Resolution convolutional neural network (SRCNN), Dual-state recurrent network (DSRN)
6	[17]	2020	Learning Texture Transformer Network for Image Super-Resolution	Texture Transformer Network for Image Super-Resolution (TTSR)

III. TECHNICAL BACKGROUND

A. Image Super resolution

The aim behind super-resolution is to create a high-resolution picture or image sequence from a series of low-resolution (noisy) photos of a scene. As a result, it makes an effort to recreate the original scene picture with high resolution from a sequence of observed photos with lesser resolution[16]. Resampling a high resolution picture produces low resolution images, according to the general technique. Once the high-resolution picture is recovered, it may be resampled to generate the low-resolution observed images using the input photos and imaging model. As a result, a bad imaging model, such as one that doesn't account for motion, will actually degrade the picture even more [17]. For example, one or more cameras may have captured the photographs or they may have been obtained from a movie. A consistent frame of reference must be established for all of these photographs. This is the registration procedure. The aligned composite picture may then be used to apply the super-resolution technique to a specific area of interest. Assembling an adequate forward picture model is critical to achieving good super-resolution. The phases of the super-resolution process are shown in the following figure 2.

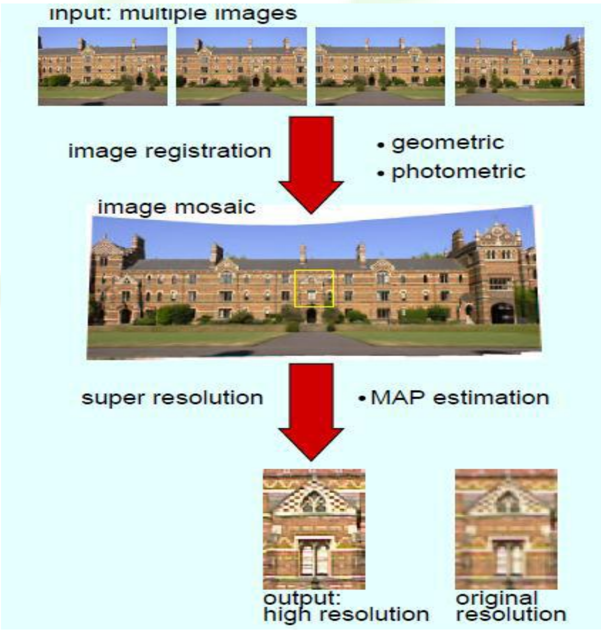

Fig 2: Stages in super-resolution [15]

B. Types of single image resolution

- **Multiple image SR**

Super-Resolution was first proposed as a set of methods for synthesizing a high-resolution image from multiple (Kl) low-resolution observations, referred to as

Multiple-Image Super-Resolution (MISR) in the following These observations are supposed to contain a slightly different version of the same scene due to perspective, rotation, translation, scale and noise. The term Super-Resolution is re-employed for the singular case of Kl = 1, referred to as Single Image Super-Resolution (SISR). As stated in the introduction of this survey, the SR problem can be seen as a linear inverse problem where a high resolution image x (or more conceptually, a scene) has been transformed through a linear transformation T into Kl low-resolution images yi.These linear transformations include spatial dimension reduction, which yields low-resolution observation vectors of size M2 < N2 . For this inverse problem to be well-posed, survey need a number Kl of low resolution observations, sufficiently large so that Kl × M2 ≥ N2. Still, the problem can be ill-conditioned (not stable under disturbed input) and require additional constraints to render a final, artefact-free HR image. The surveys address single image super-resolution. However survey here a short review of the MISR methods as SISR can sometimes be performed using the same methods, with Kl = 1, Kl being the number of LR observations[14].

- **Single image SR**

Considering the previous model of MISR, researchers focus on the case where Kl = 1; i.e. researchers only have one LR observation. In this case, only a fraction of the high-resolution information is captured. The inverse problem is therefore ill-posed and poorly conditioned, and a stable solution can only be achieved via coupled constraints on the low-resolution observation and external knowledge. This external knowledge can relax the problem, and analogue to the MISR case, supply priors that will condition the final SR image.survey organize the review via four important areas in term of past works: Edge-Directed Interpolation, gradient profile prior, Bayesian approaches, example-based approaches. The latter will be more detailed as our work focuses on such methods [13].

- **Domain-specific Super-Resolution**

In this section, the literature of text images SR and facial SR is reviewed, as some contributions of this thesis address these two domains (see chapters 4 and 5). Low-resolution texts are likely to appear in many situations (distance to the camera, tiny fonts in a scanned documents, etc.), and improving their resolution can help human readers or OCR systems that require high resolution input images. Dedicated SR methods can use priors that are specific to text images (e.g. foreground/background relationship), or use non-local assumptions such as the presence of repetitive patterns (characters, words). They are reviewed in the next subsection 3.4.1. Facial (or face) image SR is also referred to as face hallucination. Indeed, those SR algorithms have a strong a priori on the presence of a face and can “hallucinate” high-resolution faces [12].

- **Diffraction Super-Resolution**

Substituting spatial-frequency bands: Though the bandwidth allowable by diffraction is fixed, it can be positioned anywhere in the spatial-frequency spectrum. Dark-field illumination in microscopy is an example. See also aperture synthesis.

- **Multiplexing spatial-frequency bands**

An image is formed using the normal pass band of the optical device. Then some known light structure, for example a set of light fringes that is also within the pass band, is superimposed on the target.[8] The image now contains components resulting from the combination of the target and the superimposed light structure, e.g. moiré fringes, and carries information about target detail which simple, unstructured illumination does not. The “super resolved” components, however, need disentangling to be revealed [5].

- **Multiple parameter use within traditional diffraction limit**

If a target has no special polarization or wavelength properties, two polarization states or non-overlapping wavelength regions can be used to encode target details, one in a spatial-frequency band inside the cut-off limit the other beyond it. Both would utilize normal pass band transmission but are then separately decoded to reconstitute target structure with extended resolution.

- **Probing near-field electromagnetic disturbance**

The usual discussion of super-resolution involved conventional imagery of an object by an optical system. But modern technology allows probing the electromagnetic disturbance within molecular distances of the source[6] which has superior resolution properties, see also evanescent waves and the development of the new Super lens.

C. Geometrical or image-processing super-resolution

- **Multi-exposure image noise reduction**

When an image is degraded by noise, there can be more detail in the average of many exposures, even within the diffraction limit. See example on the right.

- **Single-frame deblurring**

Known defects in a given imaging situation, such as defocus or aberrations, can sometimes be mitigated in whole or in part by suitable spatial-frequency filtering of even a single image. Such procedures all stay within the diffraction-mandated pass band, and do not extend it.

- **Sub-pixel image localization**

The location of a single source can be determined by computing the "center of gravity" (centroid) of the light distribution extending over several adjacent pixels (see figure on the left). Provided that there is enough light, this can be achieved with arbitrary precision, very much better than pixel width of the detecting apparatus and the resolution limit for the decision of whether the source is single or double. This technique, which requires the presupposition that all the light comes from a single source, is at the basis of what has become known as super-resolution microscopy, e.g. stochastic optical reconstruction microscopy (STORM), where fluorescent probes attached to molecules give nanoscale distance information. It is also the mechanism underlying visual hyperacuity.

IV. RESULT PARAMETERS

There are different parameters are used to analysis the presented research work. The different result parameter are shown in this section. Also discuss the mathematical formula of those parameters.

- **PSNR**

Peak signal-to-noise ratio (PSNR) is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed as a logarithmic quantity using the decibel scale. PSNR is commonly used to quantify reconstruction quality for images and video subject to lossy compression PSNR is most easily defined via the mean squared error (MSE). Given a noise-free m×n monochrome image I and its noisy approximation K, MSE is defined as

$$\mathrm{PSNR} = 10.\log_{10}\left(\frac{MAX_I^2}{MSE}\right) \quad (1)$$

PSNR is measured in decibels (dB).

- **Mean Absolute Error (MAE)**

In statistics, mean absolute error (MAE) is a measure of errors between paired observations expressing the same phenomenon. Examples of Y versus X include comparisons of predicted versus observed, subsequent time versus initial time, and one technique of measurement versus an alternative technique of measurement. MAE is calculated as:

Formula $$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \quad (2)$$

- **Mean Square Error (MSE)**

The MSE either assesses the quality of a *predictor* (i.e., a function mapping arbitrary inputs to a sample of values of some random variable), or of an *estimator* (i.e., a mathematical function mapping a sample of data to an estimate of a parameter of the population from which the data is sampled). The definition of an MSE differs according to whether one is describing a predictor or an estimator.

Formula $$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_i - y_2) \quad (3)$$

- **Root Mean Square Error (RMSE)**

The root-mean-square deviation (RMSE) or root-mean-square error (RMSE) is a frequently used measure of the differences between values (sample or population values) predicted by a model or an estimator and the values observed. The RMSE represents the square root of the second sample moment of the differences between predicted values and observed values or the quadratic mean of these differences.RMSE is the square root of the average of squared errors. The effect of each error on RMSE is proportional to the size of the squared error; thus larger errors have a disproportionately large effect on RMSE. Consequently, RMSE is sensitive to outliers.The RMSE of an estimator {\displaystyle {\hat {\theta }}} with respect to an estimated parameter {\displaystyle \theta } is defined as the square root of the mean square error:

Formula $$\mathrm{RMSE} = \frac{\sqrt{\sum_{i=1}^{N} (x_1 - x_1)^2}}{N} \quad (4)$$

- **Structural Similarity Index Measure (SSIM)**

The structural similarity index measure (SSIM) is a method for predicting the perceived quality of digital television and cinematic pictures, as well as other kinds of digital images and videos. SSIM is used for measuring the similarity between two images. The SSIM index is a full reference metric; in other words, the measurement or prediction of image quality is based on an initial uncompressed or distortion-free image as reference. The individual comparison functions are:

Formula $$l(x,y) = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_2} \quad (5)$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2\sigma_y^2 + c_2} \quad (6)$$

$$s(x,y) = \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3} \quad (7)$$

V.CONCLUSIONS

Any-scale deep network (ASDN) is used to generate HR images of any scale with one unified network by adopting any-scale SR method, including Laplacian Frequency Representation for SR of small continuous scale ranges and Recursive Deployment for larger-scale SR.

The any-scale SR method helps to reduce the demands of training scale samples and accelerate the network convergence. The ASDN methodology can be superior to the most state-of-the-art methods on both fixed-scale and any-scale benchmarks.

REFERENCES

[1] Carlson, Ralph E., and Frederick N. Fritsch. "Monotone piecewise bicubic interpolation." SIAM journal on numerical analysis 22, no. 2 (1985): 386-400.

[2] Mort, Michael Steven. "Subpixel registration and super-resolution techniques for digital image sequence restoration." PhD diss., Southern Methodist University, 1988.

[3] Dengwen, Zhou. "An edge-directed bicubic interpolation algorithm." In 2010 3rd international congress on image and signal processing, vol. 3, pp. 1186-1189. IEEE, 2010.

[4] Madhukar, B. N., and R. Narendra. "Lanczos resampling for the digital processing of remotely sensed images." In Proceedings of International Conference on VLSI, Communication, Advanced Devices, Signals & Systems and Networking (VCASAN- 2013), pp. 403-411. Springer, India, 2013.

[5] Ren, Haoyu, Mostafa El-Khamy, and Jungwon Lee. "Image super resolution based on fusing multiple convolution neural networks." In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, pp. 54-61. 2017.

[6] Tong, Tong, Gen Li, Xiejie Liu, and Qinquan Gao. "Image super-resolution using dense skip connections." In Proceedings of the IEEE international conference on computer vision, pp. 4799-4807. 2017.

[7] Tai, Ying, Jian Yang, and Xiaoming Liu. "Image super-resolution via deep recursive residual network." In Proceedings of the IEEE conference on

computer vision and pattern recognition, pp. 3147-3155. 2017.

[8] Umehara, Kensuke, Junko Ota, and Takayuki Ishida. "Application of super-resolution convolutional neural network for enhancing image resolution in chest CT." Journal of digital imaging 31, no. 4 (2018): 441-450

[9] Zhang, Yulun, Yapeng Tian, Yu Kong, Bineng Zhong, and Yun Fu. "Residual dense network for image super-resolution." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 2472-2481. 2018.

[10] Ha, Viet Khanh, Jinchang Ren, Xinying Xu, Sophia Zhao, Gang Xie, and Valentin Masero Vargas. "Deep learning based single image super-resolution: A survey." In International Conference on Brain Inspired Cognitive Systems, pp. 106-119. Springer, Cham, 2018.

[11] Chauhan, Rahul, Kamal Kumar Ghanshala, and R. C. Joshi. "Convolutional neural network (CNN) for image detection and recognition." In 2018 First International Conference on Secure Cyber Computing and Communication (ICSCCC), pp. 278-282. IEEE, 2018.

[12] Shamsolmoali, Pourya, Xiaofang Li, and Ruili Wang. "Single image resolution enhancement by efficient dilated densely connected residual network." Signal Processing: Image Communication 79 (2019): 13-23.

[13] Ščupáková, Klára, Vasilis Terzopoulos, Saurabh Jain, Dirk Smeets, and Ron MA Heeren. "A patch-based super resolution algorithm for improving image resolution in clinical mass spectrometry." Scientific reports 9, no. 1 (2019): 1-11.

[14] Zhang, Jingzhao, Tianxing He, Suvrit Sra, and Ali Jadbabaie. "Why gradient clipping accelerates training: A theoretical justification for adaptivity." arXiv preprint arXiv: 1905.11881 (2019).

[15] Wagner, Lena, Lukas Liebel, and Marco Körner. "Deep Residual Learning For Single- Image Super-Resolution Of Multi-Spectral Satellite Imagery." ISPRS Annals of Photogrammetry, Remote Sensing & Spatial Information Sciences 4 (2019).

[16] Sonogashira, Motoharu, Michihiro Shonai, and Masaaki Iiyama. "High-resolution bathymetry by deep-learning-based image super resolution." Plos one 15, no. 7 (2020): e 0235 487.

[17] Yang, Fuzhi, Huan Yang, Jianlong Fu, Hongtao Lu, and Baining Guo. "Learning texture transformer network for image super-resolution." In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 5791-5800. 2020.

[18] Kim, Pyoung Won. "Image super-resolution model using an improved deep learning- based facial expression analysis." Multimedia Systems (2020): 1-11.

[19] Li, Kai, Shenghao Yang, Runting Dong, Xiaoying Wang, and Jianqiang Huang. "Survey of single image super-resolution reconstruction." IET Image Processing 14, no. 11 (2020): 2273-2290.

[20] Zhang, Kai, Luc Van Gool, and Radu Timofte. "Deep unfolding network for image super-resolution." In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 3217-3226. 2020.

[21] Yan, Tao, Pak Kin Wong, Hao Ren, Huaqiao Wang, Jiangtao Wang, and Yang Li. "Automatic distinction between covid-19 and common pneumonia using multi-scale convolutional neural network on chest ct scans." Chaos, Solitons & Fractals 140 (2020): 110153.

[22] Wang, Zhihao, Jian Chen, and Steven CH Hoi. "Deep learning for image super- resolution: A survey." IEEE transactions on pattern analysis and machine intelligence (2020).

[23] Wang, Chunmeng, Lingqiang Ran, and Chen He. "Fast image super-resolution with the simplified residual network." Multimedia Tools and Applications 80, no. 3 (2021): 4327- 4339.

[24] Jo, Younghyun, and Seon Joo Kim. "Practical Single-Image Super-Resolution Using Look-Up Table." In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 691-700, 2021.

[25] Han, Yuzhuo, Xiaobiao Du, and Zhi Yang. "Two-Stage Network for Single Image Super-Resolution." In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 880-887, 2021.

