ISSN: 2664-9640

Image Restoration Methods Based on Traditional Algorithms and Deep Learning

Jun Wang*, Xiaofang Liu, Xiaoli Cao

Sichuan University of Science and Engineering, Yibin, China

*Corresponding author e-mail:320085404111@stu.suse.edu.cn

Abstract

Images are one of the intuitive ways humans use to perceive the world, and low-resolution images often prevent humans from acquiring, conveying, and ex-pressing information about the characteristics of images. As image processing con-tinues to be used in various fields, the demands on image processing are increasing. Research has been conducted focusing on two areas: traditional algorithms in image restoration and super-resolution reconstruction based on deep learning. Essentially it falls under the same research objective, namely the reconstruction of lost infor-mation. Traditional image restoration algorithms are generally studied according to whether the point spread function is known in the corresponding degradation model. With the emergence of deep learning-based image super-resolution reconstruction algorithms, the field of image restoration has been provided with a technically new direction in terms of up sampling locations and up sampling methods, learning strategies, loss functions and other dimensions. This paper first reviews some tradi-tional restoration algorithms already available in academia as well as deep learn-ing-based image super-resolution reconstruction algorithms, analyses the latest re-search status, then analyses and summaries the advantages and disadvantages of these algorithms, and finally analyses the future development trends.

Keywords

Image restoration, Conventional algorithms, Deep learning, Super-resolution recon-struction

1. Introduction

Image restoration is the use of a priori knowledge of blur degradation phenomena to recover blurred and degraded images [1-2], and has a wide range of applications in the fields of medicine, criminal investigation, remote sensing analysis, and aerospace. There are various reasons for image degradation, such as image degradation due to the imaging system, object motion, lens shake and noise interference during the imaging process, so that the observed image will appear blurred and noisy relative to the real scene.

There are many algorithms for image recovery, of which traditional algorithms can recover blurred images to some extent, but only if certain a priori knowledge of the image is obtained, which is difficult to extract in real life. Images are also prone to noise during formation, acquisition and transmission, adding to the difficulty of recovery, so relying solely on traditional algorithms to deal with the results is not ideal. In recent years, with the development of technology, learning-based super-resolution algorithms are now the most mainstream algorithms. Deep learning methods [3] have shown great potential in the field of computer vision by building powerful models and designing efficient learning strategies to overcome overfitting, and neural networks have the flexibility to better fit training data by adding new non-linear activation functions or function-specific layers. More and more researchers are

therefore exploring the link between convolutional neural networks and image super-resolution. While deep learning-based super-resolution algorithms can be effective in improving resolution, the recovery accuracy is usually limited by, for example, the training samples, and is also prone to loss of feature information as the network structure deepens.

This paper will briefly introduce the respective trends of traditional image restoration algorithms and deep learning-based image super-resolution algorithms, and review some of the classical and commonly used algorithms so far, and finally give an outlook on the future research development in the direction of combining traditional algorithms with deep learning algorithms.

2. 2. Progress in the study of traditional recovery algorithms

The study of image restoration begins with the study of the degradation factors of the image and then analyses the theory related to image restoration on this basis. The whole process can therefore be modelled using Figure 1. The relationship between the observed degradation and the ideal original image can be expressed by the equation: "$F = x \otimes k + n$", F denotes the observed blurred image; “x" denotes the original image, "⊗" denotes the convolution operator, “k"denotes the point spread function which can also be called the blur kernel or convolution kernel, and “n" denotes the noise. According to the model, this is a typical linear inverse problem. Currently, conventional image restoration algorithms can be broadly classified into two categories based on whether the Point Spread Function (PSF) is known: non-blind inverse convolution algorithms where the PSF is known, and blind inverse convolution algorithms where the PSF is unknown [1].

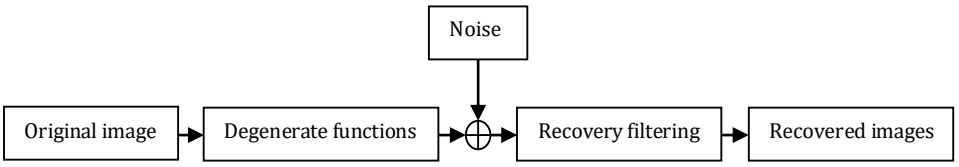

Figure 1. Image restoration model

2.1. Non-blind deconvolution algorithm

The PSF is known in the non-blind deconvolution algorithm, and a clear image is obtained by estimating the PSF using the deconvolution method to solve it. Representative are the PSF model proposed by Harris et al [4], the recovery of blurred images using experimentally calculated point expansion functions proposed by Mcglamery et al [5], the inverse filtering proposed by Helstrom et al, the minimum mean squared error filtering method [6] and the constrained least squares filtering proposed by Chan et al [7]. To balance the recovered signal and noise, Richardson [8] and Lucy [2] successively proposed the RL algorithm, whose main advantage is that it does not require any a priori information about the input image and is effective enough even in the presence of noise. As the number of iterations increased, the image details were recovered more and more clearly, but it also caused the ringing effect in the boundary regions of the image to become more and more pronounced. Later, Yuan et al [9] proposed a progressive inter- and intra-scale non-blind image deconvolution method based on the RL algorithm, using an iterative residual deconvolution in each scale to gradually recover the image details, which not only better recovers the image details but also significantly reduces the ringing artefacts. To address the noise in the smoothed region, Lee et al [10] proposed an adaptive regularized non-blind image deconvolution method that adaptively controls the

regularization strength based on local features, effectively reducing ringing and noise in the smoothed region while preserving image detail in the textured region. Subsequently, Schmidt et al [11] proposed a cascade model based on the regression tree domain, which improved image sharpness by training the model with minimal loss, but the complexity of the algorithm, and hence the amount of data, rose. To further improve in deblurring, Zhuang et al [12] proposed a new framework based on a subspace image prior, which achieved good results in terms of deblurring performance and noise robustness, the limitation of the proposed method is that it takes more time than existing deblurring methods. 2020, Yang et al [13] proposed a hierarchical Bayesian model based on a hyperparametric prior for non-blind image blurring removal algorithm, in addition to proposing an optimization algorithm with a tail recursive structure, fast running speed and low memory space occupation to speed up the convergence speed and effectively reduce the ringing effect.

Non-blind deconvolution recovery algorithms have the advantages of low implementation difficulty and low time-space complexity. However, since it cannot estimate the PSF perfectly, conventional methods to reduce these artefacts will not be able to better preserve the image details in the deconvolved image when the PSF estimation error is large.

2.2. Blind deconvolution algorithm

For the blind deconvolution recovery algorithm, since the PSF is unknown, it is necessary to first predict the PSF and secondly recover the target image with the help of the corresponding deblurring means according to the predicted PSF. According to the image degradation model, there are many different sets of clear images "x" and point spread functions "k" that can correspond to the same blurred image "F", so this is a pathological inverse problem that is difficult to solve. Earlier, Lane investigated a zero-foliage separation mechanism [14] to recover images by convolving fuzzy images of dimension greater than one and consisting of a restricted support domain and a convolution factor. Even if only a single blurred image is given, image recovery can be performed without prior knowledge of the point spread function and blind deconvolution, but it is very sensitive to noise. You et al [15] combined prior knowledge about images and PSFs and proposed an H1 paradigm minimization criterion for PSFs and clear images, which significantly improves the efficiency and simplicity of the algorithm, but the proposed method is very sensitive to local minima and the non-uniqueness of the solution have drawbacks. In 1998, Ayers published a corresponding iterative blind deconvolution algorithm [16], which involves continuously adding constraints in the null and frequency domains in a sequential manner and subsequently combining the idea of Fourier transformations to form an image prediction in subsequent iterative processing, but the method suffers from slow convergence and ambiguous solutions. Chan et al [17] introduced a total variational regularization constraint on clear images and proposed a robust and effective method for solving the minimization problem, but the convergence needs to be improved when encountering the case of highly pathologically ambiguous operators such as Gaussian blur. Subsequently, Yitzhaky [18], Rav-Acha [19] and others performed blind deconvolution recovery of images by computing parameters such as angle and direction of motion. However, it only works well for uniform linear motion blur types, so the method has significant limitations. Later, in order to better estimate the point spread function in the process of recovering out a clear image, it is usually assumed that the point spread function or the clear image meets certain assumptions, and effective models such as regularization constraint methods [20], Bayesian methods [21] and methods for edge prediction [22] have been proposed. To avoid the problem of ambiguous solutions to some extent, Krishnan et al [23] proposed regularized sparse prior, which makes the recovery process converge towards clear images, but is time-consuming and unclear for edge resolution. Yang [24] and other researchers proposed a splitting for the improved LOT(Lysaker-Osher-Tai) model in image

denoising Bregman iterative algorithm, which first solves the ROF (Rudin-Osher-Fatemi) model using the split Bregman method and then fits the LOT model using the improved split Bregman method, and experimental results demonstrate that the algorithm obtains a substantial reduction in the time to recover the image. Xu et al [25] used an L0 regularization prior, which not only provided a unified framework for uniform and non-uniform motion deblurring, but also significantly improved performance. Pan et al [26] used a dark channel prior for image restoration and achieved state-of-the-art results in deblurring natural images and performed well in a specialized approach for faces, text and low illumination conditions, which could be estimated to yield high quality sharp images.

The blind deconvolution recovery algorithm is more complex, but it is a reliable way to improve the quality of recovered images without much a priori knowledge of degradation models. There are numerous methods for blind image deconvolution and the technical algorithms are developing very rapidly, but blind deconvolution algorithms are mostly predicated on setting assumptions on images with sufficient sharpness and PSF, and subsequently adding different constraints and requirements to obtain predictions of the true image and PSF, which has certain limitations. Therefore, the problem of blind recovery of blurred images still needs further in-depth research.

3. Research progress in image restoration algorithms based on deep learning

With the rapid development of machine learning algorithms in recent years, learning-based image super-resolution algorithms have become a mainstream research direction among image restoration algorithms and have made great progress. The learning-based image super-resolution reconstruction method is mainly to first learn the image feature information in a given image dataset, then establish a priori relationship from Low Resolution (LR) images to High Resolution (HR) images, and finally realize the reconstruction of images through super-resolution image reconstruction algorithm, the reconstruction idea is shown in Figure 2 The reconstruction idea is illustrated in Figure 2. For the learning-based super-resolution algorithm, the most crucial thing is to establish a suitable learning model. According to the different learning models, learning-based image super-resolution algorithms are mainly classified into neighborhood-based embedding, sparse representation-based learning and depth-based learning [27].

3.1. Neighborhood-based embedding algorithm

The neighborhood embedding algorithm is more representative of the method proposed by Freeman et al [28-29] in 2000 to achieve image super-resolution reconstruction from low-level vision learning, which divides the image into a number of overlapping image blocks and then models the spatial relationship between HR and LR image blocks and between neighboring resolution image blocks using a Markov random field model. The method learns from a large amount of sample data to establish the mapping relationships between high and low resolution image blocks, and with the help of the model predicts the high frequency information corresponding to the low resolution image blocks. The performance of the image super-resolution algorithm is also directly affected by the size and diversity of the sample library, as the example-based learning super-resolution approach requires the creation of a large sample learning library. Inspired by learning-based methods, Chang et al [30] proposed a super-resolution algorithm for neighborhood embedding based on streaming learning, which introduces local linear embedding from popular learning into learning-based image super-resolution reconstruction. The idea of local linear embedding assumes that the data is locally linear, i.e., the data can be represented linearly using a few samples from its neighborhood, and the coefficients of this linear relationship change very little in the high-dimensional image space

and the low-dimensional image space. Thus for each input low-resolution block, K similar blocks can be found in the training sample library, and using these K similar blocks to linearly represent that low-resolution image block, the corresponding high-resolution image block can subsequently be reconstructed from the corresponding high-resolution image block. Bevilacqua et al [31] improved the constraint on weights in local linear embedding by strengthening it to a non-negative weight constraint. A non-negative least squares-based neighborhood embedding algorithm is proposed, and the final result provides good visual results, comparable to previous methods, while significantly reducing the computation time.

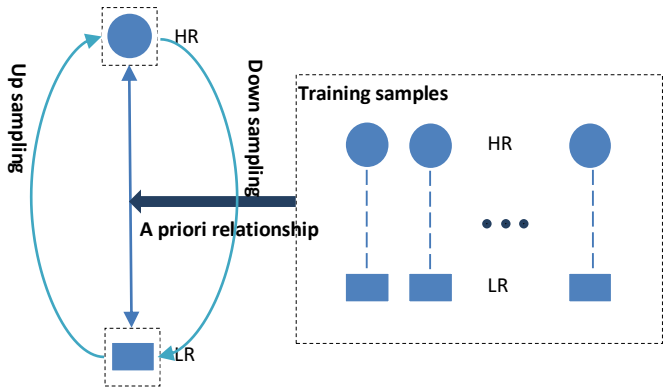

Figure 2. Idea for learning-based image reconstruction algorithm

3.2. Sparse representation-based learning algorithms

Sparse representation-based super-resolution algorithms are derived from compressive perception theory, which assumes that natural images are themselves highly correlated, i.e. that images can be sparsely represented by super-complete dictionaries. Yang et al [32-33] proposed a sparse representation-based super-resolution algorithm, which also assumes that the sparse representation relationship of dictionaries remains constant in the high- and low-resolution image space. The algorithm would thus learn a dictionary for the high- and low-resolution images separately, yielding two dictionaries in total. When reconstructing the high-resolution image, the corresponding high-resolution image block is reconstructed by finding the sparse representation coefficient of the image block in the LR image in its corresponding hyper-complete dictionary, and using this coefficient with the hyper-complete dictionary of the high-resolution image. Subsequently Zeyde et al [34] used K-singular value decomposition for learning the relevant dictionary, principal component analysis for dimensionality reduction of image features, and orthogonal matching tracking algorithm for sparse coding, which improved the performance. Dong et al [35] introduced local self-similarity regularization for the sparse representation, which can adaptively learn to select an appropriate sparse representation. Subsequently, Timofte et al [36] proposed the anchor neighborhood regression algorithm, which combines the two methods, sparse representation dictionary and neighborhood embedding, to optimize the complexity of the algorithm in dictionary learning.

3.3. Deep learning based algorithms

Deep learning based image super-resolution algorithms are becoming a hot topic of research and interest with the rapid development of convolutional neural networks. Advances in network design and design architecture are also a recent trend in deep learning, and in Super-Resolution (SR), researchers have experimented with several SR frameworks to design overall SR networks. This section discusses some basic frameworks and the latest network designs.

ISSN: 2664-9640

3.3.1. Recursive learning

The SR framework based on recursive learning, where high-level features are learned recursively using the same convolutional module and sharing parameters in the same module, is shown in Figure 3. recursive learning can be used in SR networks to control model parameters while increasing depth to improve performance and without introducing new parameters for additional convolutions, but increasing depth can also easily cause problems such as gradient disappearance or gradient explosion. Therefore, recursive learning is often used in conjunction with multi-supervised or residual learning to minimize the risk of exploding or disappearing gradients.

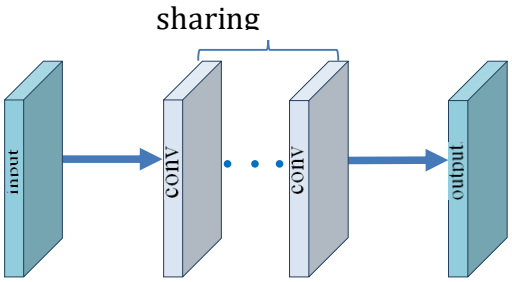

Figure 3. Recursive learning model

3.3.2. Residual learning

Residual learning avoids the complex transformation of images and only requires residual mapping to recover the lost high frequency information. Residual learning is divided into two main methods: local residual learning and global residual learning, and the residual learning model is shown in Figure 4. The local residual learning method mainly alleviates the degradation problem caused by the increasing depth of the network, and improves the learning speed and reduces the training difficulty. Global residual learning, on the other hand, is a method that correlates the input and output, where the output HR in the image SR is highly correlated with the input LR image and the model learns only the residual mapping that converts the LR image into the HR image, by generating the high frequency details that are missing in the LR image. In summary both methods use residuals to connect the input image to the output image, in the case of global residual learning, directly, and in the case of local residual learning, using local residuals to connect the input to the output using layers of different depths.

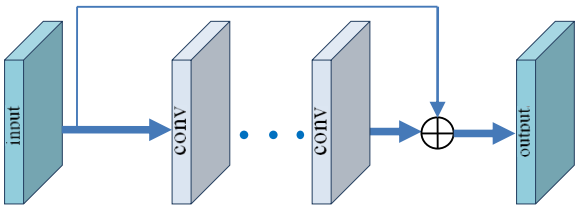

Figure 4. Residual learning model

3.3.3. The dense connection output is connected

Dense join is a solution to the problem of gradient disappearance caused by the gradient deepening of the neural network, by using the feature maps from all previous convolutional layers as input to the next layer in a feed-forward manner. In addition to alleviating the gradient disappearance problem, dense connectivity also enhances feature propagation, encourages feature reuse, and significantly reduces the number of parameters. In addition, dense concatenation is also widely used as it minimizes model size by using smaller growth rates and by using connected input feature channels, as shown in Figure 5.

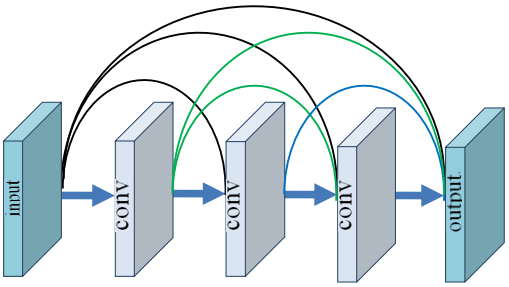

Figure 5. Dense Connection Model

3.3.4. Mechanisms of attention

In deep learning, less satisfactory results are obtained due to the fact that most neural network-based SRs ignore the relevant features of the intermediate layers resulting in smooth LR image textures. By incorporating attention learning it is possible to enhance the weight assignment of important information, focus on learning high frequency features, and reduce the learning burden of the network.

3.3.5. Review of typical algorithms

The first algorithm to apply convolutional neural networks to image SR was the SRCNN, an image super-resolution network based on the Convolutional Neural Network (CNN) proposed by Dong et al [37] in 2014. The method learns end-to-end mapping between LR and HR images directly, which is represented as a deep convolutional neural network that takes a low-resolution image as input and outputs a high-resolution image. SRCNN has only three convolutional layers, and the LR image is interpolated and amplified by a specified number of times before input to the network, so SRCNN only needs to recover the high-frequency details of the interpolated and amplified image without considering up In 2015, Wang et al [38] combined the traditional sparse coding model with deep learning to propose a sparse coding-based convolutional network, which not only reduces the complexity of the model but also has more obvious advantages in terms of recovery accuracy and human subjectivity. In 2016, Mao et al [39] proposed a very deep full convolutional encoding-decoding framework for image recovery, where the encoder consists of convolutional layers and the decoder consists of transposed convolutions. In 2016, Kim et al further increased the depth of the network and introduced residual learning, proposing the VDSR [40], VDSR uses 20 convolutional layers and residual learning makes the network easier to train improving the learning efficiency. Meanwhile, Kim et al [41] proposed the recursive convolutional network DRCN (Deeply-Recursive Convolutional Network) based on recursive learning. This network can improve performance by increasing the recursive depth and does not need to introduce new parameters for additional convolutions, but increasing the depth is also prone to problems such as gradient disappearance or gradient explosion. In 2017, Tai et al. also proposed DRRN (Deep Recursive Residual Network) [42] based on recursive learning and sharing the parameters of the recursive module that aims to achieve deep and concise networks. Specifically, global and local approaches to residual learning are used to ease the difficulty of training very deep networks, using recursive learning to control model parameters while increasing depth. In 2017, Tai [43] et al, introduced a memory module consisting of recursive and gate units to store a priori of high-resolution images. In 2016, Shi et al [44] proposed a sub-pixel convolutional layer, which differs from previous super-resolution algorithms based on interpolation amplification, and designed the first super-resolution network based on back-end amplification, ESPCNN (Efficient Sub-Pixel Convolutional Neural Network), based on a sub-pixel convolutional layer, where its input is the LR image and eventually a sub-pixel is placed at the end of the network Convolutional layers are placed at the end of the network to amplify the feature map and

generate the final high-resolution image, thus reducing the computational effort and yielding estimates with a high peak signal-to-noise ratio, but often lacking high-frequency detail in the reconstruction process, which prevents the estimates from matching the fidelity expected at higher resolutions.

These super-resolution algorithms are double the computational effort and time consuming because the image input to the network is pre-scaled to the same size as the high-resolution image. To address these issues, in 2017, Ledig et al [45] proposed a super-resolution generative adversarial network SRGAN (SR Generative Adversarial Network) by combining residual blocks [46] and adversarial learning [47]. The resulting images are more natural and realistic, while improving on the shortcomings of ESPCNNs that produce estimates with high peak signal-to-noise ratios but often lack high-frequency detail and are perceptually unsatisfactory. To further improve the performance of GAN (Generative Adversarial Network) based super-resolution algorithms, in 2018 Park et al [48] proposed the SRFeat network structure, where SRFeat not only contains an image level discriminator but also introduces a feature level discriminator, and also introduces remote layer hopping links in order to better exploit the features at different levels, enabling the generative network to generate high frequency features related to the image structure. In 2018, Zhang et al. proposed the Residual Dense Network (RDN) [51] by combining the advantages of residual blocks [49] and dense link blocks [50]. This network can deepen the network structure and increase the perceptual field while maintaining the use of the original image information to extract features directly on small-sized low-resolution images, but it is still computationally complex and time-consuming. Subsequently, Zhang et al [52] proposed a residual channel attention mechanism module to design a very deep residual channel attention network. The core idea of the attention mechanism module is to train the model to achieve better results by the network learning the feature weights according to the loss function, so that effective feature maps are weighted heavily and ineffective or less effective ones are weighted less. Of course the attention module is embedded in some of the original classification networks and inevitably adds some parameters and computational effort, but it is still acceptable in the face of the results. In 2020, Wei et al [53] proposed a divide-and-conquer model the Change Data Capture (CDC) and gradient-weighted loss of SR using three Component-Attentive Blocks (CABs) to learn attention masks and intermediate SR prediction an intermediate supervised learning strategy and train an SR model according to the principle of divide-and-conquer learning and can adapt the model training according to the reconstruction difficulty. Based on the residual channel attention network framework Niu et al [54] proposed a new Holistic Attention Network (HAN), which introduces a layer attention module to learn the weights of different layer features by considering inter-layer correlations. Also, the channel space attention module is proposed to learn the channel and spatial correlation of features at each layer, which can capture more features. Hyun et al [55] proposed the Variational Super-Resolution Network (VarSR), which generates multiple SR images to form a many-to-one relationship in order to address the single inaccuracy of the SR model results by taking samples from the potential common distribution of LR and SR images. Matching the potential distribution of LR and HR images to recover lost details. To take more account of high frequency details around edges and textures, Wang et al [56] proposed the Sparse Mask SR (SMSR) network to prune the redundant computation conditional on the input image by learning sparse masks. In 2021, Qiao et al [57] comprehensively measured the performance of existing super-resolution convolutional neural network models on microscopic image super-resolution tasks and designed a deeper Fourier channel attention network, which exploited differences in frequency content between different features to learn an accurate hierarchical representation of high-frequency information about different biological structures, achieving more robust microscopic image super-resolution predictions than other existing convolutional neural network models. To solve the problem of low dynamic range of images affecting the

image super-resolution reconstruction effect, Deng et al [58] proposed a deep coupled feedback network to achieve multi-exposure image fusion and image super-resolution simultaneously, which consists of two coupled recursive sub-networks, taking LR overexposed and underexposed images as input and then performing image fusion and super-resolution simultaneously.

For the field of image super-resolution reconstruction, the emergence of existing super-resolution reconstruction methods based on deep learning has improved the shortcomings of shallow learning methods, using the powerful fitting ability and automatic feature learning ability of convolutional neural networks, solving the problems of overfitting, gradient disappearance, explosion or parameters not self-optimizing brought about by deeper network structures, so that images can obtain more scale, detail and other information, but most of these methods However, most of these methods belong to both deep and wide deep network structures, which have problems such as the need for massive training data, high computational performance processors and the tendency of overfitting to lose high frequency detail information due to too deep networks. Therefore, further research on deep learning-based image super-resolution techniques still has great practical significance and room for development.

4. The continuation of traditional methods in deep learning approaches

In recent years some researchers have reduced the complexity of algorithms and improved efficiency by combining traditional algorithms with deep learning. In 2018, Min et al [59] combined traditional image deblurring methods with deep learning to first decompose and extract low and high frequency information using wavelet transform, and then designed a deep recurrent convolutional neural network based on recurrent convolutional neural network that can remove or weaken the high data redundancy and image smoothing brought by wavelet transform to remove corrupted image blurring by removing PSF and noise from the blurred images. The method has the ability to handle a wide range of non-blurred images and does not require expensive computational costs, but the training time is slightly longer. Vasu et al [60] proposed a convolutional neural network-based framework to deal with kernel uncertainty in non-blind motion deblurring. To remove artifacts specific to kernel noise in the deconvolution results, the paper uses existing blind deblurring methods to obtain real kernels as well as synthetically generated noisy kernels to train the network, further reducing the noise level in the kernel estimates and improving the overall recovery quality. Most of the existing models for non-blind deconvolution methods are for fuzzy kernels, which are either computationally expensive or have high memory requirements. Therefore, Wang et al [61] proposed a new generalized non-blind deconvolution model that can efficiently deconvolute different blurred kernels with only one model, predicting the residuals between the deconvoluted image and the clear image, for different kernels and different noise levels. In 2019, Jiang et al [62] proposed a model for blind recovery of super-resolution images based on chaotic neural networks, using wavelet transform to remove noise from degraded images and reduce the influence of degraded image noise on blind recovery results. The model works well with the original super-resolution image with high similarity. Subsequently, Huang et al [63] proposed a joint fuzzy kernel estimation and CNN approach for blind image recovery. Where the fuzzy kernel estimation algorithm is used for Gaussian blur, linear motion blur and out-of-focus blur, the CNN is used for iterative non-blind deconvolution to automatically learn valid image priors, outperforming traditional blind image recovery algorithms in terms of computation time and image quality in recovery. Xie et al [64] proposed a new method for adaptively learning optimal parameters for regularization in a deep network based on a full variational model. The network first uses prior knowledge to calculate regularization parameters such as deviations and weights, and then

employs the idea of deep networks to automatically update these parameters in order to avoid complex computations. The deep network based on the full variational model significantly outperforms some current methods in terms of detail retention and noise immunity, but the problem of over smoothing arises along with the high noise immunity. In 2020, Wu et al [65] integrated deep convolutional neural networks into a traditional deblurring framework by first building the Stacked Estimate Residual Net (SEN) for estimating motion flow maps and recurrent prior generation, and second building the adversarial network Recurrent Prior Generative Adversarial Net (RP-GAN) to learn the implicit images in the optimization model. The method recovers reasonable detail and shows better generalization than current state-of-the-art end-to-end based learning methods. Most existing blind image super-resolution methods assume that the blur kernel is spatially invariant over the whole image, yet the blur kernel of a real image usually changes spatially due to factors such as object motion and out-of-focus. As a result, existing blind SR methods inevitably yield poor performance in practical applications a Mutual Affine Network (MANet) for spatially varying kernel estimation was subsequently proposed by Liang et al [66] in 2021 to solve this problem. The proposed Manets not only has good performance in both spatially variable kernel estimation and invariant kernel estimation, but also achieves state-of-the-art blind SR performance when combined with non-blind SR methods.

5. Future prospects for image restoration algorithms

The improvement of image quality is currently achieved in two main ways: (1) Improving the performance of the imaging equipment, by improving the performance of the equipment directly to obtain high quality images, but at a significantly higher cost. (2) Improvement of algorithms related to image restoration. Research into algorithms is relatively outstanding in terms of applicability, practicality and affordability. Image restoration research has therefore focused on image processing algorithms, which have become increasingly sophisticated in image feature extraction and fusion, especially with the introduction of convolutional neural networks and generative adversarial networks.

This paper presents a synthesis of some algorithms in the field of traditional algorithms and in the field of super-resolution image reconstruction, and finds that the essence lies in the use of certain algorithms to improve the quality of the reconstructed image in order to recover the LR image to a HR image containing more detailed information. In addition, this paper finds it very difficult to propose algorithms that are efficient in terms of network depth, operation speed, image accuracy and time complexity, and most of the algorithms use specific images, resulting in a narrow range of applications. Therefore, future image restoration algorithms could be investigated in the following directions or perspectives: Deep learning-based super-resolution image reconstruction algorithms are able to dig deep into the detailed features of images. Complex and deep network structures such as residual networks and densely connected networks are able to extract different levels of image details and fuse them by passing them through jump connections, making some simple image features missing or ignoring the high frequency information in the image feature domain. In this regard, the independent analysis characteristics of different scale information of certain algorithms in traditional methods, the characteristics of multiple image blocks collaboratively extracting image features, the pre-learning of image information and the building of a rich image feature information library can be used to compensate for the defects of blurred image edge texture detail information blurred and missing features, reduce the complexity of the algorithm and improve the reconstruction efficiency.

References

[1] Castleman K R. Digital image processing [M]. Prentice Hall Press, 1996.

[2] Lucy L B. An iterative technique for the rectification of observed distributions [J]. The astronomical journal, 1974, 79: 745.

[3] Yu D, Deng L. Deep learning and its applications to signal and information processing [exploratory dip][J]. IEEE Signal Processing Magazine, 2010, 28(1): 145-154.

[4] Harris J L. Image evaluation and restoration [J]. JOSA, 1966, 56(5): 569-574.

[5] McGlamery B L. Computer simulation studies of compensation of turbulence degraded images[C]//Image processing. SPIE, 1976, 74: 225-233.

[6] Helstrom C W. Image restoration by the method of least squares [J]. Josa, 1967, 57(3): 297-303.

[7] Chan T F, Shen J. Image processing and analysis: variational, PDE, wavelet, and stochastic methods [M]. Society for Industrial and Applied Mathematics, 2005.

[8] Richardson W H. Bayesian-based iterative method of image restoration [J]. JoSA, 1972, 62(1): 55-59.

[9] Yuan L, Sun J, Quan L, et al. Progressive inter-scale and intra-scale non-blind image deconvolution [J]. Acm Transactions on Graphics (TOG), 2008, 27(3): 1-10.

[10] Lee J H, Ho Y S. High-quality non-blind image deconvolution with adaptive regularization [J]. Journal of Visual Communication and Image Representation, 2011, 22(7): 653-663.

[11] Schmidt U, Rother C, Nowozin S, et al. Discriminative non-blind deblurring[C]//Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2013: 604-611.

[12] Zhuang P, Fu X, Huang Y, et al. A novel framework method for non-blind deconvolution using subspace images priors [J]. Signal Processing: Image Communication, 2016, 46: 17-28.

[13] Yang H, Su X, Wu J, et al. non-blind image blur removal method based on a Bayesian hierarchical model with hyperparameter priors [J]. Optik, 2020, 204: 164178.

[14] Lane R G, Bates R H T. Automatic multidimensional deconvolution [J]. JOSA A, 1987, 4(1): 180-188.

[15] You Y L, Kaveh M. A regularization approach to joint blur identification and image restoration [J]. IEEE Transactions on Image Processing, 1996, 5(3):416-428.

[16] Ayers G R, Dainty J C. Iterative blind deconvolution method and its applications [J]. Optics letters, 1988, 13(7): 547-549.

[17] Chan T F, Wong C K. Total variation blind deconvolution [J]. IEEE Transactions on Image Processing, A Publication of the IEEE Signal Processing Society, 1998, 7(3):370.

[18] Yitzhaky Y, Mor I, Lantzman A, et al. Direct method for restoration of motion-blurred images [J]. JOSA A, 1998, 15(6): 1512-1519.

[19] Rav-Acha A, Peleg S. Restoration of multiple images with motion blur in different directions[C]//Proceedings Fifth IEEE Workshop on Applications of Computer Vision. IEEE, 2000: 22-28.

[20] Schuon S, Diepold K. Comparison of motion de-blur algorithms and real-world deployment [J]. Acta Astronautica, 2009, 64(11-12): 1050-1065.

[21] Xu Dahong. Research on image recovery algorithm based on regularization method [D]. Changsha: National University of Defense Technology, 2008.

[22] Cho S, Lee S. Fast motion deblurring [M]//ACM SIGGRAPH Asia 2009 papers. 2009: 1-8.

[23] Krishnan D, Tay T, Fergus R. Blind deconvolution using a normalized sparsity measure[C]// Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2011. IEEE, 2011: 233-240.

[24] Yang Y F, Pang Z F, Shi B L, et al. Split Bregman method for the modified lot model in image denoising [J]. Applied Mathematics and Computation, 2011, 217(12): 5392-5403.

[25] Xu L, Zheng S, Jia J. Unnatural l0 sparse representation for natural image deblurring[C]// Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2013: 1107-1114.

[26] Pan J, Sun D, Pfister H, et al. Blind image deblurring using dark channel prior[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2016: 1628-1636.

[27] Xu Zekai. Research on deep learning-based image super-resolution methods under sparse samples [D]. Hua zhong University of Science and Technology, 2019.

[28] Freeman W T, Pasztor E C, Carmichael O T. Learning low-level vision [J]. International journal of computer vision, 2000, 40(1): 25-47.

[29] Freeman W T, Jones T R, Pasztor E C. Example-based super-resolution [J]. IEEE Computer graphics and Applications, 2002, 22(2): 56-65.

[30] Chang H, Yeung D Y, Xiong Y. Super-resolution through neighbor embedding[C]//Proceedings of the 2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2004. CVPR 2004. IEEE, 2004, 1: I-I.

[31] Bevilacqua M, Roumy A, Guillemot C, et al. Low-complexity single-image super-resolution based on nonnegative neighbor embedding[J]. 2012.

[32] Yang J, Wright J, Huang T, et al. Image super-resolution as sparse representation of raw image patches[C]//2008 IEEE conference on computer vision and pattern recognition. IEEE, 2008: 1-8.

[33] Yang J, Wright J, Huang T S, et al. Image super-resolution via sparse representation [J]. IEEE transactions on image processing, 2010, 19(11): 2861-2873.

[34] Zeyde R, Elad M, Protter M. On single image scale-up using sparse-representations[C]// International conference on curves and surfaces. Springer, Berlin, Heidelberg, 2010: 711-730.

[35] Dong W, Zhang L, Shi G, et al. Image deblurring and super-resolution by adaptive sparse domain selection and adaptive regularization[J]. IEEE Transactions on image processing, 2011, 20(7): 1838-1857.

[36] Timofte R, De Smet V, Van Gool L. A+: Adjusted anchored neighborhood regression for fast super-resolution[C]//Asian conference on computer vision. Springer, Cham, 2014: 111-126.

[37] Dong C, Loy C C, He K, et al. Learning a deep convolutional network for image super-resolution[C]//European conference on computer vision. Springer, Cham, 2014: 184-199.

[38] Wang Z, Liu D, Yang J, et al. Deep networks for image super-resolution with sparse prior[C]//Proceedings of the IEEE international conference on computer vision. 2015: 370-378.

[39] Mao X, Shen C, Yang Y B. Image restoration using very deep convolutional encoder-decoder networks with symmetric skip connections [J]. Advances in neural information processing systems, 2016, 29.

[40] Kim J, Lee J K, Lee K M. Accurate image super-resolution using very deep convolutional networks[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2016: 1646-1654.

[41] Kim J, Lee J K, Lee K M. Deeply-recursive convolutional network for image super-resolution[C] //Proceedings of the IEEE conference on computer vision and pattern recognition. 2016: 1637-1645.

[42] Tai Y, Yang J, Liu X. Image super-resolution via deep recursive residual network[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2017: 3147-3155.

[43] Tai Y, Yang J, Liu X, et al. Memnet: A persistent memory network for image restoration[C]//Proceedings of the IEEE international conference on computer vision. 2017: 4539-4547.

[44] Shi W, Caballero J, Huszár F, et al. Real-time single image and video super-resolution using an efficient sub-pixel convolutional neural network[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2016: 1874-1883.

[45] Ledig C, Theis L, Huszár F, et al. Photo-realistic single image super-resolution using a generative adversarial network[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2017: 4681-4690.

[46] Ganin Y, Lempitsky V. Unsupervised domain adaptation by backpropagation[C]//International conference on machine learning. PMLR, 2015: 1180-1189.

[47] Goodfellow I, Pouget-Abadie J, Mirza M, et al. Generative adversarial nets [J]. Advances in neural information processing systems, 2014, 27.

[48] Park S J, Son H, Cho S, et al. Srfeat: Single image super-resolution with feature discrimination[C]//Proceedings of the European conference on computer vision (ECCV). 2018: 439-455.

[49] He K, Zhang X, Ren S, et al. Deep residual learning for image recognition[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2016: 770-778.

[50] Huang G, Liu Z, Van Der Maaten L, et al. Densely connected convolutional networks[C]// Proceedings of the IEEE conference on computer vision and pattern recognition. 2017: 4700-4708.

[51] Zhang Y, Tian Y, Kong Y, et al. Residual dense network for image super-resolution[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2018: 2472-2481.

[52] Zhang Y, Li K, Li K, et al. Image super-resolution using very deep residual channel attention networks[C]//Proceedings of the European conference on computer vision (ECCV). 2018: 286-301.

[53] Wei P, Xie Z, Lu H, et al. Component divide-and-conquer for real-world image super-resolution[C]// European Conference on Computer Vision. Springer, Cham, 2020: 101-117.

[54] Niu B, Wen W, Ren W, et al. Single image super-resolution via a holistic attention network[C]//European conference on computer vision. Springer, Cham, 2020: 191-207.

[55] Hyun S, Heo J P. VarSR: Variational super-resolution network for very low resolution images[C]// European Conference on Computer Vision. Springer, Cham, 2020: 431-447.

[56] Wang L, Dong X, Wang Y, et al. Learning Sparse Masks for Efficient Image Super-Resolution [J]. 2020.

[57] Qiao C, Li D, Guo Y, et al. Evaluation and development of deep neural networks for image super-resolution in optical microscopy [J]. Nature Methods, 2021, 18(2): 194-202.

[58] Deng X, Zhang Y, Xu M, et al. Deep coupled feedback network for joint exposure fusion and image super-resolution [J]. IEEE Transactions on Image Processing, 2021, 30: 3098-3112.

[59] Min C, Wen G, Li B, et al. Blind deblurring via a novel recursive deep CNN improved by wavelet transform [J]. IEEE Access, 2018, 6: 69242-69252.

[60] Vasu S, Maligireddy V R, Rajagopalan A N. Non-blind deblurring: Handling kernel uncertainty with cnns[C]//Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2018: 3272-3281.

[61] Wang R, Tao D. Training very deep CNNs for general non-blind deconvolution [J]. IEEE Transactions on Image Processing, 2018, 27(6): 2897-2910.

[62] Jiang C, Chen Q. Construction of blind restoration model for super-resolution image based on chaotic neural network [J]. Chaos, Solitons & Fractals, 2020, 131: 109498.

[63] Huang L, Xia Y. Joint blur kernel estimation and CNN for blind image restoration [J]. Neurocomputing, 2020, 396: 324-345.

[64] Xie S, Zheng X, Shao W Z, et al. Non-blind image deblurring method by the total variation deep network [J]. IEEE Access, 2019, 7: 37536-37544.

[65] Wu J, Di X. Integrating neural networks into the blind deblurring framework to compete with the end-to-end learning-based methods [J]. IEEE Transactions on Image Processing, 2020, 29: 6841-6851.

[66] Liang J, Sun G, Zhang K, et al. Mutual affine network for spatially variant kernel estimation in blind image super-resolution[C]//Proceedings of the IEEE/CVF International Conference on Computer Vision. 2021: 4096-4105.