Retraction Notice

The Editor-in-Chief and the publisher have retracted this article, which was submitted as part of a guest-edited special section. An investigation uncovered evidence of systematic manipulation of the publication process, including compromised peer review. The Editor and publisher no longer have confidence in the results and conclusions of the article.

QX, GZ, and HC agree with the retraction.

Super-resolution generative adversarial networks using autoencoder reduce dimension

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Abstract. Generative adversarial network (GAN) has been widely applied to produce super-resolution (SR) image with real perception and texture details. In most existing SR approaches, the training objective typically measures a pixel-wise average distance between the SR and high-resolution (HR) images. However, as the degradation function of different images from HR to low resolution (LR) is generally different, optimizing such metrics often leads to certain unpleasant artificial traces. Unlike the prevalent GAN inversion methods that require expensive image-specific optimization at runtime, we present an alternative formulation by directly leveraging latent representation produced by a pretrained AutoEncoder. We call this improved method reduce dimension super-resolved GAN (RD-SRGAN). RD-SRGAN first obtains the latent feature representation of LR image by a pretrained AutoEncoder as input to the generator network. This process not only reduces noise effects but also decreases the overall computational complexity. On the other hand, the residual between the ground truth and the produced images replaces the produced images as input to the discriminator network, and a 2D zero mean Gaussian noise with controllable low variance replaces the real images as another input to the discriminator network. By leveraging the feature representation and properties of the 2D zero mean Gaussian noise, we restrict the optimization space to produce an SR image. Therefore, the residual of the generated SR images tend to approximates to a Gaussian noise, which introduces useless deviation information as little as possible. Experimental results show that RD-SRGAN can benefit from these strategies and achieve improved fidelity and naturalness comparison to existing methods. Switching the pretrained AutoEncoder allows the method to deal with images from diverse categories, e.g., remote sensing satellite imaging, medical imaging, and astronomy. © *2023 SPIE and IS&T* [DOI: 10.1117/1.JEI.32.6.062504]

Keywords: super-resolution; autoencoder; reduce dimension; generative adversarial networks.

Paper 220840SS received Aug. 18, 2022; accepted for publication Nov. 29, 2022; published online Jan. 4, 2023.

1 Introduction

Image resolution is related directly to the information presentation ability and size of an image. The image super-resolution (SR) technology aims at promoting image resolution from lower resolution original image, and it has practical value in many fields, such as improving the clarity of old images, enhancing the resolution of remote sensing images, and improving the efficiency and accuracy of medical image SR reconstruction in disease diagnosis.[1–3] With the vigorous development of the Internet, the demand for improved image and video quality continues to grow, and SR image reconstruction technology has aroused extensive research interest.

The generative adversarial network (GAN) has been widely used in SR, which has an advantage in texture details of generated image. One common way to undertake the SR task is to first train a generator network and then perform adversarial training with a discriminator network to distinguish the upscaled images between the real images. Another approach is GAN inversion, which needs to map a corrupted image back to the latent space. Although various network architectures and training strategies continuously promote the quality of output images, the recovery

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effect of images still needs to be improved, as some SR results tend to be too smooth and lose details while others introduce too many artifacts. This is because these methods generally measures a pixel-wise average distance between the SR and high-resolution (HR) images through mean-square-error loss and assesses visual quality of the reconstructed images by peak signal-to-noise ratio (PSNR) criteria. In fact, it leads to a solution that is essentially weighted pixel-wise average of the set of realistic images corresponding to the low-resolution (LR) image. Meanwhile, as image SR reconstruction is an inverse problem, there may be diverse HR images corresponding to one LR image, and the SR image "generated" from LR image is only one of all possible HR images. Therefore, the exact degree of difference between the generated SR image and the real HR image is still unknown although the image produced by the GAN-based method looks more natural. The distinctions between the generated image and the true one may introduce unknown cognitive risks in some sensitive fields, such as remote sensing satellite image or medical image analysis, thus limiting the application of such SR methods in these domains. Moreover, training of the above methods is usually time-consuming as high dimension of image.

In this paper, we mainly focus on the artifacts problem in GAN-based SR image. Distinguishing it from the previous methods, the input of discriminator network is redefined to reduce artifacts of the SR image by minimizing statistically significant distribution differences between the image produced by generator network and the HR image. Moreover, we use the image feature latent representation fetched by a pretrained AutoEncoder as input of generator network, which is conducive to decrease noise impact and speed up training. The nonreference measures index natural image quality evaluator (NIQE) is used to evaluate the perceptual effect of the produced image and prove the effectiveness of the proposed method.

2 Related Work

2.1 *Image Super-Resolution*

Image SR reconstruction techniques can be partitioned into two categories: one is reconstruction through multiple LR images and the other for a single LR image. Some widely image resolution improvement methods based on interpolation technology, such as nearest-neighbor interpolation and bicubic interpolation, essentially leverage a fixed convolution kernel to deal with LR images, and although they have a relatively fast processing speed, there still needs to be improved in image detail restoration and resolution. The deep learning-based image SR reconstruction technology, which mainly considers single image super-resolution (SISR) method, can directly learn the end-to-end SR mapping function of LR images through neural network training. Image super-resolution using deep convolutional networks (SRCNN)[4] is an earlier work in this domain. Zhang et al.[5] proposed an effective residual density network, which can fetch multilevel features of images for generation of SR image. Lim et al.[6] discussed the influence of the batch norm (BN) layer on the quality of image generation and put forward an enhanced deep residual network for SISR model to improve the training process and performance. Since the memory and computation of CNN-based SR will grow quadratically with the input size, it is necessary to research SR acceleration method to meet the requirements of real-time image implementation. Kong et al.[7] decomposed the large image into subimages, and then used the classification module to classify the subimages into different categories according to the degree of restoration difficulty, and applied different SR modules. Since most of the molecular images would pass through a smaller network, the computation amount could be saved up to 50%. Although the accuracy and speed of SISR obtained using deep convolutional neural networks have been greatly improved, the texture details of the generated SR images are still unsatisfactory.

2.2 *Generative Adversarial Networks*

Since GAN with deep model can generate HR images, GAN have been applied in many domains, such as image generation and deblurring.[8,9] At present, SR image-generation model based on GAN framework can restore photorealistic textures from deeply downsampled images.

Ledig et al.[10] applied generative adversarial network proposed to SISR and proposed SRGAN model. In SRGAN, the weighted sum of discriminator loss and traditional perceived loss is taken as model loss. Meanwhile, image features in the visual geometry group (VGG)[11] network layer space are constructed as perceptual loss, and the discriminator is trained to identify the difference between the reconstructed SR image and the target HR image. Through adversarial training, the generator network can well produce SR image, which has closer visual effect to the natural image in the detailed texture and is more suitable for visual perception of human eyes. Wang et al.[12] proposed enhanced super-resolution generative adversarial networks (ESRGAN), which adopted the relative adversarial generation network and VGG features before the activation function to further promote the detail and reality sense of the produced images. Shang et al.[13] introduced receptive field block into ESRGAN. It effectively balanced the problem of small computation and large receptive field and can extract very detailed features, and further improved the reconstruction effect of the produced SR images details, so as to achieve the 16× SR reconstruction. PULSE[14] generates SR images by unsupervised learning mode in the hidden code space of a pretrained styleGAN to find the image that is closest to LR. However, PULSE sometimes fails to recover the structure of the ground truth since the low-dimensional latent constraints are not enough to direct the restoration process. At the same time, its execution is carried out in an iterative manner, which is time-consuming.

2.3 *AutoEncoder*

In machine learning problems, there exist many high-dimensional data that often involve redundancy information, which will reduced the accuracy of a classification model if directly using such high-dimensional data.[15] As an unsupervised learning model, AutoEncoder is an effective method for data dimension reduction (DR) and feature extraction, thus widely applied in image reconstruction and noise reduction.[16,17] Based on the improved GAN, Pidhorskyi et al.[18] proposed a novel Adversarial Latent Autoencoder, which achieves the same generation ability as GAN and can learn decoupling representation. Recently, there has been a proliferation of ways to perform image editing by pretrained GANs. As StyleGAN provides a very rich latent space for expressing image features, Tov et al.[19] designed an encoder for image manipulating and controlling on the latent space of StyleGAN and achieved superior real-image adjustment ability with a small reconstruction accuracy descend. GLEN[20] leverage an encoder-bank-decoder architecture where bank is a pretrained StyleGAN to provide very rich priors space for expressing different features, which enables the network to generate real details and retain the characteristics of the ground truth at the same time.

3 Proposed Method

Our primary goal is to ameliorate the visual effect of generated SR image and reduce the overall computational complexity. In this section, we begin by describing the network architecture of our approach, then present new perceptual loss of the discriminator, and finally propose a modified discriminator training strategy based on analysis on input sample distribution to reduce artifacts.

3.1 *Network Architecture*

As SRGAN and ESRGAN have a good performance in HR image generation, we mainly refer their network structure (Fig. 1) to design our implementation framework for SR images task. Two major improvements have been made. (1) In view of the fact that the discriminator is easy to under-train for the high-dimensional input data, which lead to insufficient training of the generator and result in the degradation of generated image quality, we adopt a pretrained AutoEncoder to fetch the latent representation of the input image and then train the GAN with the DR latent representation. (2) As for the discriminator, the object to be distinguished is changed from the generated image and real image to a 2D zero mean Gaussian noise and the residual between the generator image and the ground truth [Figs. 1(b)].

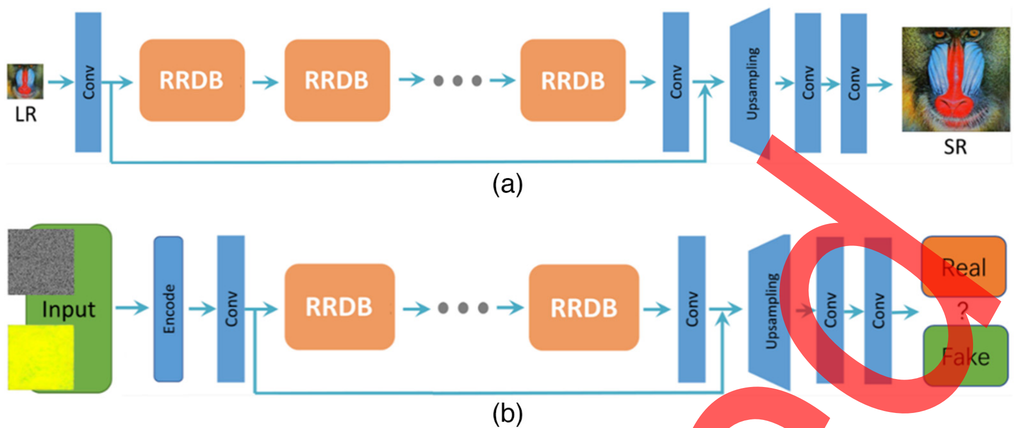

Fig. 1 (a) Generator network uses residual-in-residual dense block. (b) Discriminator network compares the difference of distribution between image residual and Gaussian noise, so that the image generated by the generator does not introduce additional information.

3.2 *Dimension Reduction*

Because the probability distribution of the real images and that of the generated samples is difficult to have an intersection point in the high-dimension space; therefore, the distance of the probability distribution of the two calculated by Jensen–Shannon (JS) divergence is identical to zero. Therefore, the discriminator can almost always discriminate discrepancy between the real image and the produced one by accurately classifying the probability distribution, which lead to the optimization of discriminator and generator lost its meaning, as no matter how hard the generator is trained, it cannot produce a sample that is close to the true probability distribution, which reduces the quality of generated image.

Image is a typical high-dimensional data (e.g., $64 \times 64 \times 1$ image has 4096 dimensions), and SR image generation algorithm based on GAN also have to face the same problem mentioned above. Different from WGAN which use Wasserstein distance to replace JS distance,[21] we used a pretrained AutoEncoder to extract the feature representation of high-dimensional image.[22] AutoEncoder worked in an unsupervised learning mode, and its structure is shown in Fig. 2.

Advantages. The use of latent representation can capture feature of images and reduce the interference of noise with the aid of image sparsity. Moreover, it has low computational complexity by reducing data dimension.

3.3 *Noise Input*

The common paradigm of GAN's discriminator, such as SRGAN and ESRGAN, is trained with the goal of distinguishing the real images and the produced images as possible. This training

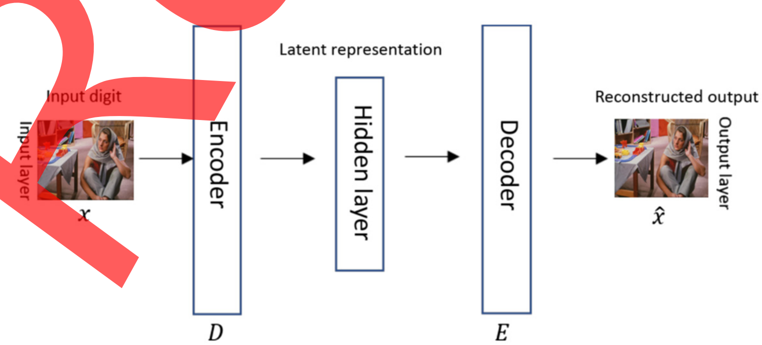

Fig. 2 A schematic of a pretraining AutoEncoder with input, encoding layer, hidden layer, decoding layer, and output.

strategy tries to make the distribution of produced images approximate distribution of the ground truth, but it cannot control the difference characteristics between their distributions. Therefore, it is difficult to avoid the occurrence of unpredictable content, namely artifacts, in generated images. To control these artifacts, we put forward transforming the input of the discriminator to a 2D zero mean Gaussian noise with controllable low variance as well as residual between the generated image and the ground truth.

Advantages. The change of input for discriminator aims to train the discriminator recognizing the discrepancy between the distribution of image residual and a 2D zero mean Gaussian noise with controllable low variance, which enables the generator to learn to produce images closer to the ground truth not only in distribution of content but also in avoiding introducing additional information into generated image as possible as the discrepancy between the two can be limited to be a low variance 2D zero mean Gaussian noise without excrescent information,[17] so as to effectively reduce the introduction of artifacts.

3.4 *Perceptual Loss*

In this work, the DR content loss function [Eq. (1)] is proposed to better describe image content features, and the adversarial loss on the residual describes the image space more than the pixel space, thus improving the texture detail.

The perceptual loss L^{SR} is vital for network performance. Like Lim et al.[6] and Wang et al.,[12] we define the perceptual loss to be the weighted sum of the content loss (L_p, L_1) and the adversarial loss L_x^{Ra}. The perceptual loss corresponds to the restoration of image content, whereas the adversarial loss corresponds more to the restoration of image texture. The total loss of the generator is

$$L_G = L_p + \lambda L_G^{\mathrm{Ra}} + \eta L_1, \tag{1}$$

where L_p is calculated according to feature map obtained by the real images and the generate images that passed through the pretrained VGG19 network (before the ReLU activation layer), respectively:

$$L_p = \mathbb{E}_e \|\phi_{i,j}(\mathrm{encode}(x^{\mathrm{HR}})) - \phi_{i,j}(\mathrm{encode}(G(x^{\mathrm{LR}})))\|_2. \tag{2}$$

Here e denotes the code word of image x obtained by the AutoEncoder. x^{HR} denotes the code word of a high-resolution image. x^{LR} denotes the code word of a low-resolution image. Encode$(\cdot)$ denotes the encoding part of the AutoEncoder. $G(\cdot)$ is generator network mapping. $\phi_{i,j}$ is a map fetched from the j'th convolution (after activation) before the I'th maxpooling layer within the VGG19 network.

$L_1 = \|\mathbb{E}_{x_i} G(x_i) - y\|_1$ is the 1-norm distance between the restored image $G(x_i)$ and the ground-truth image y. λ and η is the weighting coefficient of each loss item. The relative adversarial loss of the generator network L_G^{Ra} is defined as follows:

$$L_G^{\mathrm{Ra}} = -\mathbb{E}_{e_r}[\log(1 - D_{\mathrm{Ra}}(e_r, e_f))] - \mathbb{E}_{e_f}[\log(D_{\mathrm{Ra}}(e_r, e_f))]. \tag{3}$$

The relative adversarial loss of the discriminator is

$$L_D^{\mathrm{Ra}} = -\mathbb{E}_{e_f}[\log(1 - D_{\mathrm{Ra}}(e_f, e_r))] - \mathbb{E}_{e_r}[\log(D_{\mathrm{Ra}}(e_f, e_r))]. \tag{4}$$

Here e_r denotes the code words of a Gaussian noise and $e_f = \mathrm{encode}(G(x^{\mathrm{LR}}))$ denotes the code words of the generated image.

4 Experiments

4.1 *Training Parameter*

We used the Keras to build our network and train the network with batch size 8 on NVIDIA T4 GPU. The HR images have the shape of $256 \times 256 \times 3$. Like SRGAN and ESRGAN, a scaling factor of 4 is applied to resized HR images to obtain LR images for all experiments.

The training procedure is divided into two steps. In the first step, an AutoEncoder with the shape of the output of hidden layer 4×8 is trained. Then dimension reduced features representation of the LR image are obtained through the encoder as input to the generator. In the second step, we calculate residual between the ground truth and the generated images as one input to the discriminator and use a 2D zero mean Gaussian noise having the same dimension with the residual as another input. The generator and discriminator network are trained according to the loss in Sec. 3.4. We set the training parameters as $\lambda = 5 \times 10^{-3}$. and $\eta = 10^{-2}$, the learning rate as 10^{-4} and the training epoch as 30,000. The Adam optimizer was used to train the network.

4.2 *Data and Similarity Measure*

We use the datasets Div2K,[23] Celeba,[24] Flickr2K,[25] and outdoor scene training[26] for training. The test dataset adopted the widely used standard datasets Set5[27] and Set14.[28] PSNR and SSIM indices are used applied to assess the image distortion. Considering that PSNR and SSIM did not conform to the subjective evaluation of human observers, we alternatively use the nonreference measurement method NIQE[29] to evaluate and compare the image perception quality.

4.3 *Qualitative Results*

In this section, the SRGAN and ESRGAN are compared with our method in generating SR images. The numerical results of PSNR/SSIM/NIQE are exhibited in Table 1, and visual effect of some representative produced image is shown in Fig. 3.

It can be seen in Fig. 3 that although the result of ESGAN seems has more image details and texture, it actually generate artifacts, while the presented reduce dimension super-resolved GAN (RD-SRGAN) outperform the other image SR methods by seeking a balance between image details and accuracy of approximating the ground truth.

Table 1 Comparison of SRGAN-VGG54, ESRGAN, RD-SRGAN, and the original HR images of benchmark data (4× upscaling).

Set 5	SRGAN	ESRGAN	RD-SRGAN	HR
PSNR	27.98	28.42	28.49	
SSIM	0.81	0.82	0.83	1
NIQE	5.44	5.27	5.06	5.83
Set14				
PSNR	24.27	24.30	24.58	
SSIM	0.67	0.67	0.68	1
NIQE	4.25	4.38	4.12	5.09
BSD100				
PSNR	23.76	23.95	24.14	
SSIM	0.63	0.64	0.66	1
NIQE	4.83	4.27	4.05	4.34

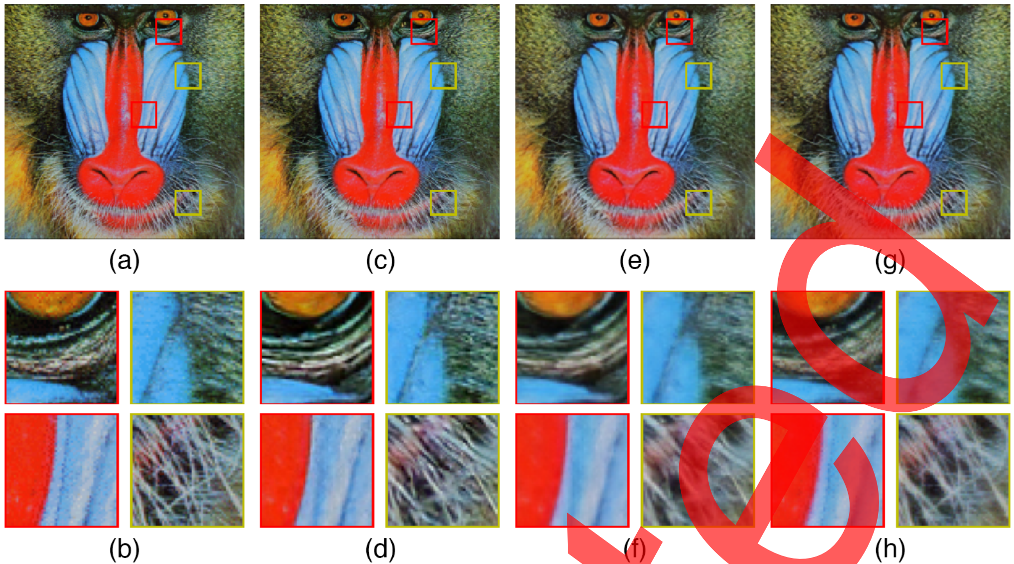

Fig. 3 (a), (b) HR; (c), (d) ESRGAN; (e), (f) SRGAN; and (g), (h) RD-SRGAN.

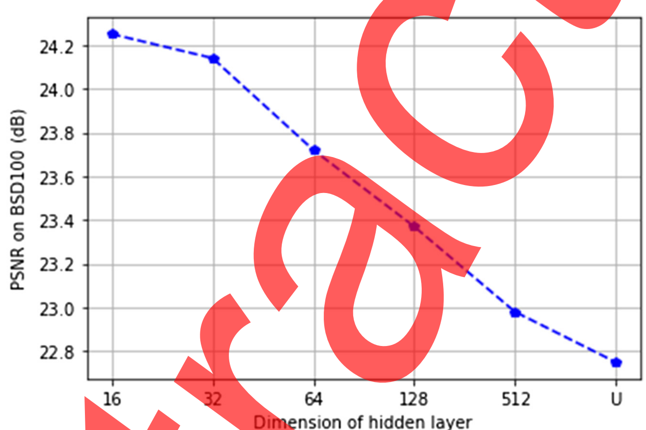

Fig. 4 Dependence of network performance (PSNR) on dimension of hidden layer.

We further research the influence of the AutoEncoder hidden layer dimension on the performance of RD-SRGAN (BSD100 for 4× SR), and the results are exhibited in Fig. 4. It is observed that RD-SRGAN achieves optimal performance when the latent representation dimension equal to 16, and the performance gradually decreases with the increase of the dimension. This result shows that there exists a lot of redundant information in images, and using the latent representation instead of image as input can further reduce noise impact so as to improve the quality and fidelity of the generated images. Moreover, the computational complexity of the conceptual model is effectively reduced due to the reduction of the input dimension.

5 Conclusion

In this paper, we have proposed a methodology (RD-SRGAN) for image SR task by exploiting a pretrained AutoEncoder to capture the latent representation of image and redefining the input of discriminator network to control the introduction of artifacts in generated SR images. RD-SRGAN can produce credible and satisfactory SR reconstructed image with low computational complexity compared with those recently proposed methods. Through employing specific pretrained AutoEncoder, our method has application potential in different image task fields, such as remote sensing satellite imaging, medical imaging, and astronomy, which has high credibility requirements for SR image.

Acknowledgments

This work was funded by the Doctoral Research Startup Foundation of Wuchang Shouyi University (No. B20200301). The authors have no conflicts of interest to declare that are relevant to the content of this article. All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Qian Xiang and Guo-hua Zhao. The first draft of the manuscript was written by Qian Xiang and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Availability of Data and Material

The data used to support the findings of the research are included within this manuscript.

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