

SRPGAN: Perceptual Generative Adversarial Network for Single Image Super Resolution

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Abstract

Single image super resolution (SISR) is to reconstruct a high resolution image from a single low resolution image. The SISR task has been a very attractive research topic over the last two decades. In recent years, convolutional neural network (CNN) based models have achieved great performance on SISR task. Despite the breakthroughs achieved by using CNN models, there are still some problems remaining unsolved, such as how to recover high frequency details of high resolution images. Previous CNN based models always use a pixel wise loss, such as l_2 loss. Although the high resolution images constructed by these models have high peak signal-to-noise ratio (PSNR), they often tend to be blurry and lack high-frequency details, especially at a large scaling factor. In this paper, we build a super resolution perceptual generative adversarial network (SRPGAN) framework for SISR tasks. In the framework, we propose a robust perceptual loss based on the discriminator of the built SRPGAN model. We use the Charbonnier loss function to build the content loss and combine it with the proposed perceptual loss and the adversarial loss. Compared with other state-of-the-art methods, our method has demonstrated great ability to construct images with sharp edges and rich details. We also evaluate our method on different benchmarks and compare it with previous CNN based methods. The results show that our method can achieve much higher structural similarity index (SSIM) scores on most of the benchmarks than the previous state-of-art methods.

1. Introduction

Single image super resolution (SISR) is a well defined problem in computer vision area. It tries to reconstruct a high resolution image from a single low resolution image. It has been a very attractive research topic over the last two decades [7] [1] [8]. Since SISR can restore some high frequency details, it has been applied to many practical appli-

cations such as medical imaging [25], satellite imaging [27], and face identification [3], where rich details are greatly desired.

In recent years, CNNs have shown powerful ability to learn highly non-linear transformations. Due to their powerful learning ability, the CNN based methods are widely used for SISR tasks and have achieved remarkable progress. Despite those breakthroughs brought by the CNN based methods, there are still some critical problems, which remain largely unsolved, such as how to recover high resolution image with high perceptual quality and high frequency details. A common objective function of previous CNN based methods is the pixel wise loss function between the reconstructed and the ground truth high resolution images. The most commonly used pixel wise loss is l_2 loss. A method based on l_2 loss is to minimize the mean square loss and maximize the peak signal-to-noise ratio (PSNR), which is a common measure used to evaluate SISR algorithms. Although such a method leads to high performance on PSNR metric, the images always tend to be blurry and over-smoothing [26] [4]. Some recent literatures have pointed out that the pixel wise loss based methods failed to build multimodal distribution [26] [4] [32]. There are two different approaches to solve this issue. One approach is to use a different constructed method, for example PixelCNN [4], to build dependencies between different pixels. The other is using perceptual loss and adversarial learning to generate more realistic images [18]. In this paper, we focus on the latter approach.

In this work, we propose a general SISR framework (SRPGAN), which is based on the Image-to-Image model [12]. The start point of the proposed framework is the generative adversarial network (GAN). Unlike some previous methods [18], which uses a classification network to generate the perceptual loss, we use the features obtained by the discriminator network to build a more robust perceptual loss. We further design the adversarial loss and the content loss to build the final objective function. We also propose to use the Charbonnier loss function as the content loss function, which is different from the previous methods. In

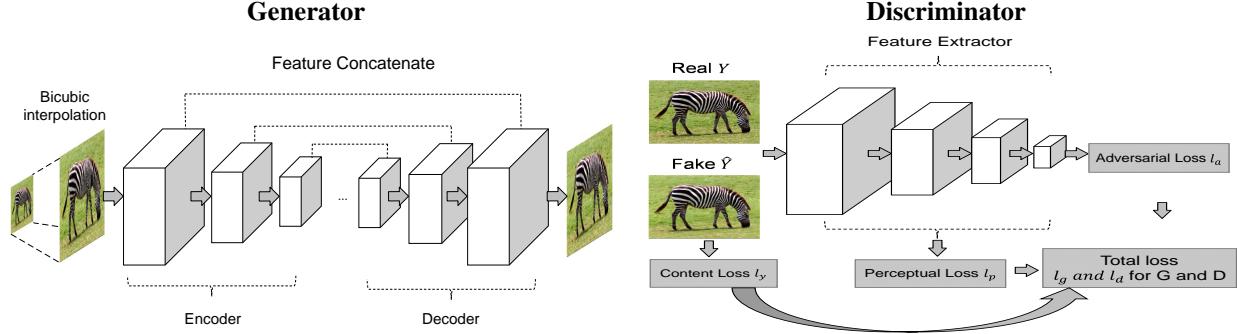


Figure 1. The structure of the SISR framework(SRPGAN). Our Framework consists of a generator G (left) and a discriminator D (right). The generator part generates high resolution image from low resolution one. The discriminator takes the generated image and the ground truth image as inputs to extract features of these inputs. Based on these extracted features, the discriminator can build the objective functions for D and G .

respect of the network architecture, we propose to replace the batch normalization layer with the instance normalization layer. We evaluate our method on most used benchmarks with a large upscaling factor. Our method outperforms other previous methods with SSIM score on most of benchmarks. Beside the quantitative evaluation, our method has also demonstrated great ability to reconstruct images with rich details and high perceptual quality.

The rest of this paper is organized as follows. The related work part summarizes the previous related works briefly. The methods section describes the framework details and the proposed individual loss functions. The quantitative evaluation and results visualization can be found in the experiments section.

2. Related Works

From the great performance achieved by the deep convolutional neural network at ImageNet challenge, various CNN based methods are applied to the super-resolution problem. SRCNN is the first paper that applies CNN to the single image super-resolution problem [5]. SRCNN is a simple model with three convolutional layers working for feature extraction, non-linear mapping, and image reconstruction. This method learns the end-to-end transformation between low and high resolution images.

Based on the results of SRCNN, the authors accelerated the previous model by using an hour-glass shape CNN structure, and achieved a better SR performance and a real-time SR model with the rate higher than 24 fps on a generic CPU [6]. To achieve a real-time model for SR, they replaced the bicubic interpolation part in the previous model with deconvolution layers. After removing bicubic interpolation, this model can learn directly from the low resolution image. FSRCNN model only includes convolution layers and deconvolution layers. The convolution layers share the weights for different upscaling factors. With weight shar-

ing, FSRCNN is able to deal with various scales using a single model.

Because of its success at the ImageNet challenge, the deep architecture similar with VGG net was proposed for large receptive fields in the VDSR (Very Deep network for Super-Resolution) [14]. The convergence rate is the main limitation of the deeper model. The VDSR tries to use a higher learning rate of 10^{-1} while SRCNN used a learning rate of 10^{-5} . Due to the high learning rate, it can be easier to diverge. By using the gradient clipping, the VDSR can be controlled strictly. The VDSR included the concept of residual learning to generate final output results. Due to the property of SISR problem, the output image is quite similar to the input image. With the concept of residual learning, the input image is added to the output of the model before making the final output image. As a result, the model can focus on the detail with high-frequency components. Besides, DRCN(Deeply-Recursive Convolutional Network) based on the VDSR model added recursion connections for weight sharing and model compression with only 5 layers [15]. The LapSRN is the one of the most recent frameworks for SISR problem [17]. The model includes a cascaded framework of feature extraction and image reconstruction parts using laplacian pyramids. And the Charbonnier loss function is used instead of the $L2$ loss function.

By replacing deconvolution layers with sub-pixel convolutional layers, the total computational complexity can be reduced dramatically. The new operator can also generate a cleaner image without checkerboard artifacts. With the efficient operation, ESPCN(Efficient Sub-Pixel Convolutional Neural Network) has achieved significant $\times 10$ speed up which can be applied for SR operation of HD videos on a single GPU [24].

The methods we mentioned above are always based on pixel wise loss, such as $L2$ loss. Although such a method leads to a high PSNR score, the images constructed by that

always tend to be blurry and over-smoothing. Some recent works also have point out that pixel wise loss fails to capture multimodal distribution [4]. There are two approaches to solve this issue. One approach is to use different network structures to construct high resolution images. For example, in [4], the authors proposed the PixelCNN to capture the dependencies between different pixels. Another approach is to combine the perceptual loss and GAN model to generate more realistic and sharper image. In this paper, we mainly focus on the latter approach. There are also some recent papers which focus on the perceptual loss. In [13], the authors firstly introduced the perceptual loss based on VGG classification network for the style transformation and super resolution. The SRGAN method combines perceptual loss and adversarial loss for photo-realistic image [18]. They address that the pixel wise loss does not capture the perceptual difference between ground truth images and output images. However, the perceptual loss in these paper is based on the VGG classification network, such a naive classification network cannot capture the desired high frequency details in super resolution tasks and will introduce extra computation. To this end, the VGG perceptual loss is not a suitable metric for SISR. In this paper, we try to build a more robust perceptual loss to get higher perceptual quality.

3. Methods

3.1. SISR Framework

We build our single image super resolution framework on Image-to-Image model [12]. Our framework consists of an image generator G and a discriminator D . The generator is trying to transform the image in the domain generated by bicubic upsampling to the image in the ground truth high resolution image domain. The discriminator is trying to extract the features of the input high resolution images and the constructed images. Based on the features obtained by the discriminator, we can get the adversarial loss and the perceptual loss. Finally, we combine these two loss functions with the content loss to build the total objective functions of D and G . The overall framework is illustrated in Figure1.

Considering a single low-resolution image, we firstly upscale it by the specified factor using bicubic interpolation for further computing. Then, the generator network takes the interpolated image as the input and maps it to a high resolution image. Our final goal is to train a generator network G that can generate high resolution image that is as similar as possible to the ground truth high resolution image. To achieve this, we construct a robust loss using the output and the intermediate features obtained by the discriminator D . Additionally, we design a content loss which can be used for evaluating the similarity between the generated image and the ground truth image. The individual loss functions are described with more details in the following subsection.

3.1.1 Network architecture

Our start point is the Image-to-Image model [12], we further tailor the Image-to-Image model for the SISR task. To the best of our knowledge, this is the first paper that attempts to apply the image-to-image model to the SISR task.

The generator G is the core of the whole framework. The structure of G illustrated in Figure1(left) has an encoder-decoder shape. We add skip connections following the general shape of the U-Net [22] to combine the local and global information. Specifically, in our generator, skip connection is implemented by concatenating features obtained by layer i and layer $n - i$, where n is the total number of the convolution layers. The encoder part of G consists of a stack of convolution layers. More Specifically, we use convolution layers with small 3×3 kernels. Following the previous work [18], we use the stride convolution to reduce the image resolution in each encoder layer, instead of the max pooling. Further more, we replace the batch normalization layers with the instance normalization layers [29] to achieve better performance. In Figure2, we show the difference between the convolution blocks in a traditional GAN model and those in our model. We increase the resolution of the input features with transpose convolution layers in the decoder part. For the activation functions, we use the LeakyReLU activation functions in all encoder and decoder layers. We build the patch discriminator network follow-

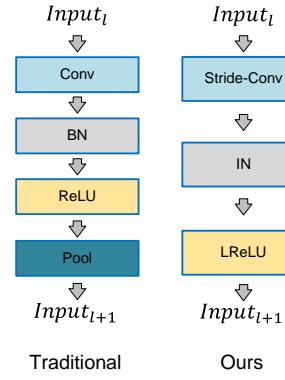


Figure 2. Comparison of a conv block in a traditional GAN model and that in our model. Our model replaces the pooling layer with a stride-convolution layer. And we use the instance normalization (i.e. IN), not the batch normalization.

ing [12]. Compared with the traditional discriminator, the patch discriminator tries to classify whether each patch in an image is real or fake instead of the whole image. Such a discriminator can restrict the GAN model to focus on the high frequency details. And the existence of the content loss can make sure the correctness of the low frequency part. The detail of the loss functions can be found in the following subsection. In the convolution blocks of the discriminator, we remove the batch normalization layers directly.

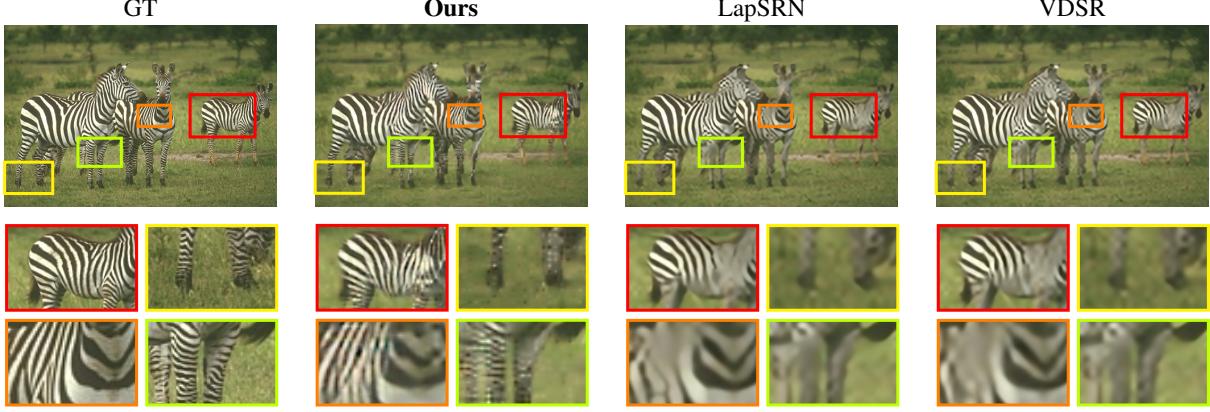


Figure 3. Reconstruction results [4 \times upscaling] of **Ours** and recent state-of-the-art methods(LapSRN and VDSR). We use color boxes to highlight sub regions which contain rich details. We magnify the sub regions in the bellow boxes to show more details. From the sub region images, we can see that our method has stronger ability to recover high frequency details and sharp edges.

3.1.2 Instance normalization

Although batch normalization [11] has been proved to be effective on many image classification tasks, recent works [20] [29] have pointed out that batch normalization will decrease the performance of image generation tasks. In [29], the authors proposed to use the instance normalization instead of batch normalization on the image style transform task. Following this, we replace the batch normalization layers with instance normalization layers to get better performance on SISR tasks. Instance normalization is to apply the normalization on a single image instead of the whole batch of images. To introduce the formulation, we denote $x \in R^{T \times C \times W \times H}$ as an input batch which contains T images. Let x_{tkij} denote the tkj -th element, where i and j are the spatial dimensions, k is the input feature channel, and t is the index of the image in the batch. Then the formulation of the instance normalization is given by:

$$y_{tkij} = \frac{x_{tkij} - u_{tk}}{\sqrt{\sigma_{tk}^2 + \epsilon}} \quad (1)$$

where $u_{tk} = \frac{1}{HW} \sum_{l=1}^W \sum_{m=1}^H x_{t k l m}$ and $\sigma_{tk}^2 = \frac{1}{HW} \sum_{l=1}^W \sum_{m=1}^H (x_{t k l m} - u_{tk})^2$.

We replace batch normalization with instance normalization in every layer of the generator G . The instance batch normalization layer can achieve better performance than batch normalization, and it also can be used for preventing the divergence of the training.

3.2. Loss Functions

In this section, we will introduce the formulas of the loss functions. To get the objective loss functions of discriminator and generator, we need to design adversarial loss, content loss and perceptual loss, respectively. We can get these

individual loss functions based on the outputs and intermediate features obtained by discriminator D .

3.2.1 Adversarial loss

Our generator G tries to learn a mapping from the image z by bicubic interpolation to the ground truth high resolution image y . We design our discriminator D in a conditional GAN fashion. The adversarial loss function of our GAN model can be expressed as below:

$$\begin{aligned} l_a(G, D) = & E_{z, y \sim p_{\text{data}}(z, y)} [\log D(z, y)] + \\ & E_{z \sim p_{\text{data}}(z)} [\log (1 - D(z, G(z)))] \end{aligned} \quad (2)$$

In the training phase, the discriminator D tries to minimize this objective function and the generator G tries to maximize it. Compared with the unconditional GAN, the formulation of the adversarial loss function in the unconditional GAN can be expressed as below:

$$\begin{aligned} l(G, D) = & E_{y \sim p_{\text{data}}(y)} [\log D(y)] + \\ & E_{z \sim p_{\text{data}}(z)} [\log (1 - D(G(z)))] \end{aligned} \quad (3)$$

In contrast, the discriminator of unconditional GAN cannot observe the input bicubic image z .

The adversarial loss can encourage our generator to generate the solution that resides on the manifold of the ground truth high resolution images by trying to fool the discriminator.

3.2.2 Content Loss

The adversarial loss can be helpful to recover the high frequency details. Except for the high frequency part, we also need to design a content loss to ensure the correctness of the low frequency part of the constructed image. The commonly used content loss is the mean square loss. In this paper, we propose to use the Charbonnier loss [2] to achieve

better performance on the SISR task. We denote y as the ground truth high resolution image and $G(z)$ as the constructed image. The Charbonnier loss can be expressed as below:

$$l_y(y, \hat{y}) = E_{z,y \sim p_{data}(z,y)}(\rho(y - G(z))) \quad (4)$$

Where $\rho(x) = \sqrt{x^2 + \epsilon^2}$ is the Charbonnier penalty function. To give a comparison, we also try the 11 loss and 12 loss in the experiments.

3.2.3 Perceptual Loss

Previous methods based on the pixel-wise loss always generate images that lack high frequency details. Some perceptual loss based on VGG16 network has been proposed to deal with this issue. Instead of using the perceptual loss based on the VGG16 classification network, we use the intermediate features of the discriminator to build the perceptual loss. We can get a more robust perceptual loss for image super resolution by that. Additionally, we can reduce the computation budget of the perceptual loss through the reuse of the extracted features obtained by the discriminator. To introduce the formula of the perceptual loss, we denote ϕ_i as the feature map computed by the i -th convolution layer(after the activation function layer) within the discriminator. Then, we can define the perceptual loss as:

$$l_p = \sum_{i=1}^L E_{z,y \sim p_{data}(z,y)}(||\phi_i(y) - \phi_i(G(z))||) \quad (5)$$

In this formula, each term in the equation measures the 11 loss of features extracted by i -th layer of the discriminator D , where the $G(z)$ represents the image constructed by the generator G .

3.2.4 Optimization

We use an alternative optimization way to optimize the generator G and discriminator D . Based on the individual loss functions presented above, we can define the objective functions for discriminator D and generator G . The formulas are defined as :

$$l_d = -l_a(G, D) + \lambda l_p \quad (6)$$

$$l_g = l_a(G, D) + \lambda_1 l_p + \lambda_2 l_y \quad (7)$$

In the training phase, we minimize l_d with respect to the parameters of discriminator D and minimize l_g with respect to the parameters of generator G . To optimize our networks, we alternate between one gradient descent step on D and one step on G . For optimizing solver, we use the ADAM algorithm for both G and D . The details can be found in the experimental section.

4. Experiments

4.1. Training Details

For training dataset, we use images from T91, BSDS200 [19] and General100 datasets. In each training batch, we randomly select 64 image patches as the high resolution patches, with each patch in the size of 128×128 . We obtain the low resolution patches by downsampling the high resolution patches using the bicubic kernel with specified downsampling factor. We augment the training data in the following ways: (1) Random Rotation: Randomly rotate the images by 90 or 180 degrees. (2) Brightness adjusting: Randomly adjust the brightness of the images. (3) Saturation adjusting: Randomly adjust the saturation of the images. We pre-process all the images by dividing the image data by 255. Finally, we get about 640 thousand patches for training.

We initialize the parameters using "Xavier" [9]. We train our model from scratch with ADAM optimizer by setting $\beta_1 = 0.9$, $\beta_2 = 0.99$, and $\epsilon = 10^{-8}$. The learning rate is initialized as 10^{-4} and the learning rate decreased to 10^{-5} while we finished 10^6 iterations. We set the weight term in the loss function as $\lambda = 0.01$ in equation(6), $\lambda_1 = 1$ and $\lambda_2 = 1$ in equation(7). Our implementation is based on Tensorflow. We have trained 3 models for scaling factor of 2, 4, 8 respectively. It takes about 18 hours for training one model on one GTX1080.

4.2. Quantitative Evaluation

We evaluate the performance of our method on five benchmarks: SET5, SET14, BSDS100, URBAN100, and MANGA109. The metrics we used are PSNR and SSIM [30]. We compare the proposed method with previous state-of-the-art SISR methods. For scaling factors, we test our model on 2x,4x and 8x. Table1 shows the overall quantitative comparisons for 2x, 4x and 8x. Most of the results of other methods are cited from [17] and [15]. Because our method dose not optimize the mean square loss directly, the PSNR score of our method is much lower than other methods. Other than that, our method tends to generate more realistic images and recover more details than the state-of-the-art methods as shown in Figure3. On the other hand, our method is competitive on the mean SSIM score which has been shown to correlate with human perception on different benchmarks. Our SRPGAN method performs favorably against existing methods on the most used benchmarks with different scaling factor (2x,4x and 8x). From the results, our method has a poor performance on the MANGA dataset, the main reason is that our training dataset consists of real life images and our GAN model tend to reconstruct realistic images, but the MANGA dataset is a dataset consisting of Japanese comics. For other benchmarks, our methods have obvious improvements on SSIM score.



Figure 4. Reconstruction results of **Ours** and recent state-of-the-art methods.[$4\times$ upscaling]

Algorithm	Scale	SET5	SET14	BSDS100	URBAN100	MANGA109
		PSNR / SSIM				
Bicubic	2	33.65 / 0.930	30.34 / 0.870	29.56 / 0.844	26.88 / 0.841	30.84 / 0.935
A+ [28]	2	36.54 / 0.954	32.40 / 0.906	31.22 / 0.887	29.23 / 0.894	35.33 / 0.967
SRCNN [5]	2	36.65 / 0.954	32.29 / 0.903	31.36 / 0.888	29.52 / 0.895	35.72 / 0.968
FSRCNN [6]	2	36.99 / 0.955	32.73 / 0.909	31.51 / 0.891	29.87 / 0.901	36.62 / 0.971
SelfExSR [10]	2	36.49 / 0.954	32.44 / 0.906	31.18 / 0.886	29.54 / 0.897	35.78 / 0.968
RFL [23]	2	36.55 / 0.954	32.36 / 0.905	31.16 / 0.885	29.13 / 0.891	35.08 / 0.966
SCN [31]	2	36.52 / 0.953	32.42 / 0.904	31.24 / 0.884	29.50 / 0.896	35.47 / 0.966
VDSR [14]	2	37.53 / 0.958	32.97 / 0.913	31.90 / 0.896	30.77 / 0.914	37.16 / 0.974
DRCN [16]	2	37.63 / 0.959	32.98 / 0.913	31.85 / 0.894	30.76 / 0.913	37.57 / 0.973
LapSRN [17]	2	37.52 / 0.959	33.08 / 0.922	31.80 / 0.895	30.41 / 0.910	37.27 / 0.974
SRPGAN (Ours)	2	29.67 / 0.950	27.66 / 0.911	27.89 / 0.901	30.41 / 0.892	37.27 / 0.943
Bicubic	4	28.42 / 0.810	26.10 / 0.704	25.96 / 0.669	23.15 / 0.659	24.92 / 0.789
A+ [28]	4	30.30 / 0.859	27.43 / 0.752	26.82 / 0.710	24.34 / 0.720	27.02 / 0.850
SRCNN [5]	4	30.49 / 0.862	27.61 / 0.754	26.91 / 0.712	24.53 / 0.724	27.66 / 0.858
FSRCNN [6]	4	30.71 / 0.865	27.70 / 0.756	26.97 / 0.714	24.61 / 0.727	27.89 / 0.859
SelfExSR [10]	4	30.33 / 0.861	27.54 / 0.756	26.84 / 0.712	24.82 / 0.740	27.82 / 0.865
RFL [23]	4	30.15 / 0.853	27.33 / 0.748	26.75 / 0.707	24.20 / 0.711	26.80 / 0.840
SCN [31]	4	30.39 / 0.862	27.48 / 0.751	26.87 / 0.710	24.52 / 0.725	27.39 / 0.856
VDSR [14]	4	31.35 / 0.882	28.03 / 0.770	27.29 / 0.726	25.18 / 0.753	28.82 / 0.886
DRCN [16]	4	31.53 / 0.884	28.04 / 0.770	27.24 / 0.724	25.14 / 0.752	28.97 / 0.886
LapSRN [17]	4	31.54 / 0.885	28.19 / 0.772	27.32 / 0.728	25.21 / 0.756	29.09 / 0.890
SRPGAN(Ours)	4	22.68 / 0.880	22.50 / 0.786	23.91 / 0.749	20.00 / 0.763	21.00 / 0.860
Bicubic	8	24.39 / 0.657	23.19 / 0.568	23.67 / 0.547	20.74 / 0.515	21.47 / 0.649
A+ [28]	8	25.52 / 0.692	23.98 / 0.597	24.20 / 0.568	21.37 / 0.545	22.39 / 0.680
SRCNN [5]	8	25.33 / 0.689	23.85 / 0.593	24.13 / 0.565	21.29 / 0.543	22.37 / 0.682
FSRCNN [6]	8	25.41 / 0.682	23.93 / 0.592	24.21 / 0.567	21.32 / 0.537	22.39 / 0.672
SelfExSR [10]	8	25.52 / 0.704	24.02 / 0.603	24.18 / 0.568	21.81 / 0.576	22.99 / 0.718
RFL [23]	8	25.36 / 0.677	23.88 / 0.588	24.13 / 0.562	21.27 / 0.535	22.27 / 0.668
SCN [31]	8	25.59 / 0.705	24.11 / 0.605	24.30 / 0.573	21.52 / 0.559	22.68 / 0.700
VDSR [14]	8	25.72 / 0.711	24.21 / 0.609	24.37 / 0.576	21.54 / 0.560	22.83 / 0.707
LapSRN [17]	8	26.14 / 0.738	24.44 / 0.623	24.54 / 0.586	21.81 / 0.581	23.39 / 0.735
SRPGAN(Ours)	8	19.14 / 0.743	19.10 / 0.635	21.55 / 0.613	17.68 / 0.607	18.68 / 0.730

Table 1. Quantitative evaluation of state-of-the-art SR algorithms: average PSNR/SSIM for scale factors $2\times$, $4\times$ and $8\times$. **Red** text indicates the best SSIM score and **blue** text indicates the second best performance of SSIM score.

4.3. Visualizations

In the context of perceptual quality, our method can recover realistic textures from heavily down-sampling images on the public benchmarks. We have selected some im-

ages from the benchmarks to visualization the effective of our method in Figure3 and Figure4. From the results, the images constructed by our method have shown significant gains in perceptual quality.

We have conducted a series experiments to show the ef-

fectiveness of our proposed SISR framework and loss functions. In Figure3, we compare our method with previous state-of-the-art methods LapSRN [17] and VDSR [14]. Except for these two methods, we have also compared our method with other CNN based methods. We just list the results of these two methods due to the page limitation. To better visualize the effectiveness of our method, we selected small regions which contain rich details in the images to magnify. As the Figure3 shows, our method successfully reconstructs stripes on Zebra’s bodies (shown in red and orange boxes). On the other hand, LapSRN and VDSR based on a pixel-wise loss just generate blurry images without stripes in that area. In the leg area(yellow and green box), the perceptual quality of our method is not good enough, but our method tries to recover the stripe details on the leg, the other methods just construct leg images without any details. We also compare with other CNN based methods, such as SRCNN [5]. In contrast, our approach surpasses other state-of-the-art methods to generate richer texture details. Further examples of perceptual improvements can be found in Figure4. For these images, we can see that our method has constructed high resolution images with good perceptual quality, those methods which are based on pixel-wise loss have generated blurry and over-smooth images.

4.4. Analysis of loss function

Except for comparison with other methods, we also evaluate the performance of the generator network without our perceptual loss or replacing the Charbonnier loss with other pixel-wise loss, such as l2 loss. We firstly train a model without perceptual loss. The quantitative results are summarized in Table2 and the visualization results are in Figure5. From the Table2, the proposed framework with perceptual loss achieves much better performance than trained without perceptual loss. From Figure5 the model trained with perceptual loss has a better perceptual quality than the model trained without perceptual loss. We can observe from the sub images that our method trained with perceptual loss can accurately reconstruct the beards of the baboon(in red box).

Dataset	Perceptual loss	SSIM
Set14	Yes	0.786
Set14	No	0.754
BSDS100	Yes	0.749
BSDS100	No	0.716

Table 2. Quantitative comparison of different perceptual loss strategies. We can get a better performance with our robust perceptual loss.

We also compare our perceptual loss with the SRGAN which is based on the VGG perceptual loss (see more details in the follow subsection).

Dataset	Content Loss	SSIM	Training epochs
Set14	Charbinnier	0.786	100
Set14	11	0.782	100
Set14	12	0.763	100

Table 3. Quantitative comparison of different content loss.

We have conducted further experiments to explore the content loss. To validate the effect of the Charbonnier loss function, we trained a model with l2 content loss respectively. Through the experiments, the model with l2 content loss requires more training epochs to achieve comparable performance than the model trained with the Charbonnier content loss. The results are shown in Table3.

4.5. Comparison with SRGAN

We conduct experiments to compare our method with the SRGAN [18] based on the VGG perceptual loss. We can see that our perceptual loss is more robust than the VGG perceptual loss (see in Figure5). Note that we have trained a SRGAN model using the open source Tensorflow code on Github¹. For fair comparison, we train the SRGAN model using the same training dataset as our own method. In the training phase, we train that on a scaling factor of 4x for 100 epochs which is the same as our method.

As we can see in Figure5, our SRPGAN method does a better job at reconstructing fine details, such as the beards of the baboon (in red boxes of the second and the fourth columns), leading to pleasing visual results. On the other hand, in the training phase, our SRPGAN does not need an extra VGG classification net to build the perceptual loss, compared with the SRGAN method. This may help to reduce the computation budget while training.

4.6. Limitations

While our model is capable of constructing realistic images with sharp edges and rich details on a large scale factor(4x, 8x). There are still some limitations of our methods. One limitation of our GAN based model is that the constructed images have checker board artifacts at the pixel level. The artifacts are visible in Figure5 upon magnification of the sub image regions. This phenomenon is also mentioned in many previous literatures [21]. To solve this issue, one can replace the transpose convolution with resize convolution [21] and sub-pixel convolution [24]. We mark this as a part of future work.

5. Conclusion

In this paper, we have highlighted some limitations of the pixel wise loss based methods. To solve these issues, we propose a general framework based on generative and adversarial network (GAN) for single image super resolution.

¹<https://github.com/zsdonghao/SRGAN>

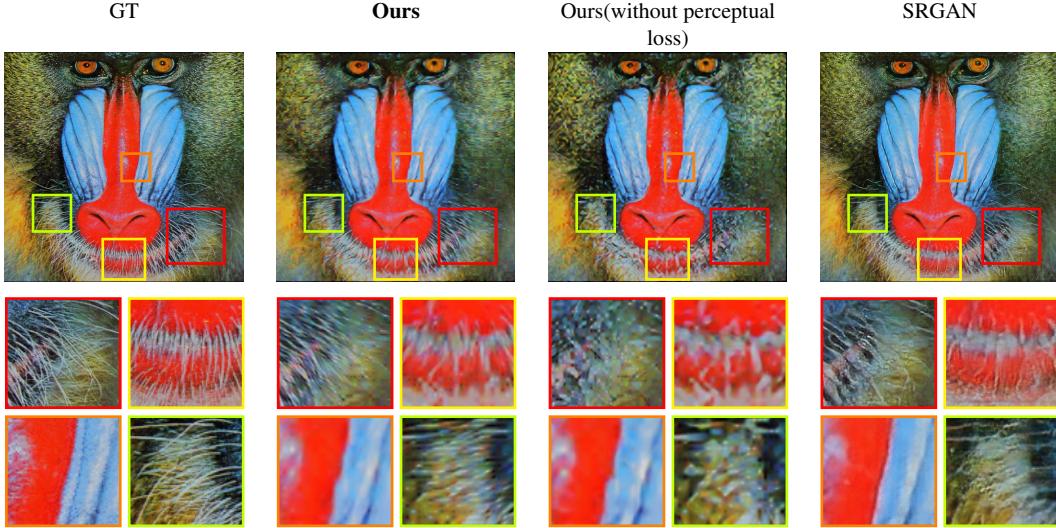


Figure 5. Reconstruction results [4x upscaling] of different perceptual loss strategy (our framework with proposed perceptual loss (the second column), our framework without perceptual loss(the third column), SRGAN with VGG perceptual loss(the fourth column))

Based on the framework, we design individual loss functions and combined them to form the objective functions for discriminator and generator respectively. Our method achieves the highest SSIM score on most of commonly used benchmarks, and also construct images with better perceptual quality than previous methods, especially for large upscaling factors (4x and 8x). The quantitative and visualization results have shown that SRPGAN surpasses previous methods on details recovering and perceptual quality.

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