Photo-Realistic Continuous Image Super-Resolution with Implicit Neural Networks and Generative Adversarial Networks

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Abstract

The implicit neural networks (INNs) can represent images in the continuous domain. They consume raw (X, Y) coordinates and output a color value. Therefore they can represent and generate images at arbitrarily high resolutions in contrast to convolutional neural networks (CNNs) that output a constant-sized array of pixels. In this work, we show how to super-resolve a single image using an INN to produce sharp and photo-realistic images. We employ a random patch-based coordinate sampling method to obtain patches with context and structure; we use these patches to train the INN in an adversarial setting. We demonstrate that the trained network retains the desirable properties of INNs while the output is sharper compared to previous work. We also show qualitative and quantitative comparisons with INN and CNN baselines on benchmark datasets of DIV2K, Set5, Set14, Urban100, and B100. Our code will be made public at [https://github.com/iSarmad/CiSRGan](https://github.com/iSarmad/CiSRGan).

1 Introduction

Image enhancement and super-resolution find applications in various consumer products such as smartphone photography, TV and video, etc. The advent of deep learning and neural networks has enabled advancements in single-image super-resolution (SISR). Convolutional neural networks (CNNs) are the most popular method for SISR [11]. However, the output of CNNs is an array of pixels with a fixed size. Therefore, we need to train a new network for different scaling factors. This strategy can be very inconvenient and time-consuming.

Recently a class of neural networks called implicit neural networks (INNs) has gained attention [33, 25, 28]. These networks can represent an image by storing the color value of each pixel corresponding to a given pixel coordinate [26, 31]. This image representation leads to a continuous model where one can zoom in to a single image arbitrarily by changing the discretization level of the input coordinates.

Chen et al. [8] proposed an INN based method called local implicit image function (LIIF) for SISR. They used a single INN to perform SISR for any scale and achieved arbitrary zooming capability i.e. given a neural network that was trained for scales in the range of 1x to 4x (we refer to this range as in-scale), their model can perform super-resolution on 6x and 8x etc (out-of-scale). This ability to extrapolate makes LIIF very beneficial for super-resolution. Furthermore, LIIF is on par with CNNs in terms of distortion metrics such as the PSNR [22]. Despite these advantages, LIIF suffers from blurry outputs for out-of-scale super-resolution due to the use of pixel-wise loss function. In this work, we propose continuous image super-resolution generative adversarial network (CiSRGAN) that trains INNs in an adversarial setting for super-resolution, thus improving the perceptual quality and photo-realism of output for out-of-scale SISR. To the best of our knowledge, training implicit network for the task of out-of-scale single image super-resolution in an adversarial setting has not been proposed before.

We compare our method with previous state of the art in INN and CNN based super-resolution methods.
2 Related Works

Convolutional Neural Network based SISR

Before convolutional neural networks (CNNs) [18, 19, 13], handcrafted algorithms were used to perform single image super-resolution (SISR); e.g., Yang et al. [39] used sparse coding to solve this task. Recently, SISR using CNN has become mainstream [20, 27, 23, 37]. SISR can be divided into algorithms that either focus on lowering distortion or improving perceptual quality [6]. Our work focuses on improving the perceptual quality.

Implicit Neural Networks for SISR

Implicit neural networks (INNs) have recently become popular as a way to represent continuous images and shapes [26, 38, 4, 9, 3, 10]. Occupancy Networks [25] and Deep SDF [28] used INNs for 3D shape representation. Then Sitzman et al. [31], and Tancik et al. [34] showed that the INNs could also be used to represent images with high fidelity. Later works learned GANs using INNs [7, 32, 30, 2]. Local implicit image function (LIIF) [8] recently showed that continuous representation could also be used to perform SISR. The resulting SISR model is agnostic to resolution, and a single model can be used to super-resolve images to any required resolution. LIIF [8] uses the $L_1$ loss to train the network, which renders the output blurry. However, we train our model in the adversarial setting to perform photorealistic SISR and achieve a better result.

3 Method

Consider a low-resolution 2D Image $I_{ls}$ that consists of arrays of pixels. The high resolution 2D image corresponding to $I_{ls}$ is given as $I \rightarrow (x, y) \in \mathbb{R}^{X \times Y}$. Where $I_{ls}(x, y) \in \mathbb{R}^{X \times Y}$, and $s$ is the scaling factor. Each pixel in $I$ has coordinates $x$ and $y$. Let’s assume that a continuous image can be represented by a function $f_\theta$. Then the discrete image $I$ can be represented as:

$$I = f_\theta(c, z),$$

(1)

$z$ is the latent vector of the features of low-resolution image $I_{ls}$. Note that $c = x_{hr} - v$, $x_{hr}$ are the pixel coordinates of image $I$ and $v$ are the coordinates of the feature vector $z$ in the image domain. In this work, $f_\theta$ is the implicit neural (INN).

**Training LIIF in an Adversarial Setting**

An overview of our approach is shown in Figure. 1. The input image is passed through a convolutional encoder to obtain a latent vector $z$. This latent vector $z$ and the image $I$ coordinates $x_{hr}$ are used to obtain the color values of the pixels at input coordinates $x_{hr}$ using LIIF block [8]. Note that the INN consists of a few multilayer perceptron (MLP) layers that are present inside the LIIF block. We need an output image patch to train the INN using adversarial and perceptual loss. The previous method [8] uses a random set of coordinates from the image. This sampling method works well when the objective is to minimize the pixel-wise loss, e.g., $L_1$. However, looking at only pixels means the contextual information is lost. Therefore, we propose a random patch-based sampling procedure instead of a random point-based sampling method to retain contextual information. We first train LIIF [8] with random patches instead of random points with only a pixel-wise loss. We notice that this random patch-based sampling method performs similar to a random coordinate-based sampling method.
in terms of performance.

We use the $L_1$ loss following previous work \[8\], which trains with only the $L_1$ objective leading to smooth images which blur the textural information for out-of-scale super-resolution.

The use of a patch-based sampling procedure permits the use of adversarial loss that is based on generative adversarial network (GAN) \[12\]. The GAN consists of a generator and a discriminator that compete against each other. The goal of the generator is to generate realistic images, whereas the goal of the discriminator is to get good at classifying generated images as fake. In this joint training, both get better, resulting in realistic image generation. However, instead of using a standard GAN formulation, we use a relativistic GAN formulation instead \[18\]. This formulation is different from the standard discriminator, which estimates the probability that an input image is real. Instead, the discriminator predicts the probability that a real image is relatively more realistic than a fake one. We define a discriminator network $D_{θ_D}$, which is optimized in an alternating manner along with generator network $G_{θ_G}$ to solve the adversarial min-max problem. The relativistic GAN solves the following min-max problem:

$$\min_{θ_G} \max_{θ_D} \mathbb{E}_X [\log D_{θ_D}(I^{GT}, G_{θ_G}(I_{train}))] + \mathbb{E}_X [\log (1 - D_{θ_D}(G_{θ_G}(I_{train}), I^{GT}))]$$

(2)

Note that, $X = (I^{GT}, I_{train}) \sim (p_{train}(I^{GT}), p_{G}(I_{train}))$ and $D_{θ_D}(I^{GT}, G_{θ_G}(I_{train})) = \sigma(C(I^{GT}) - \mathbb{E}_{Gθ_{G}(I_{train})}[C(G_{θ_G}(I_{train}))])$.

Where $\mathbb{E}_{Gθ_{G}(I_{train})}[.]$ is mean over the generated data in the mini-batch. $\sigma$ is the sigmoid activation function and $C$ is the output of discriminator before the activation function. For details, we refer to \[16\].

We also use the perceptual loss that is the distance between the features of a pre-trained VGG network between the predicted image $I$ and the ground-truth image $I^{GT}$ \[15\]. The complete training objective for the generator is as follows:

$$L_1 = \lambda_1 L_1 + \lambda_2 L_G + \lambda_3 L_{VGG}$$

(3)

Where $L_1, L_G$ and $L_{VGG}$ are the content, adversarial and perceptual losses respectively. The $λ_1, λ_2$ and $λ_3$ are weighting hyperparameters terms for each of the objectives respectively. We set them following guidelines from previous work \[37\].
Figure 2: **Out-of-Scale Qualitative Comparison on DIV2K**: This figure shows the reference image from DIV2k, the low-resolution input image (LR), super-resolved image using LIIF \[8\] and finally our model’s output (CiSR-GAN). LR images are 6x and 12x down-sampled from ground-truth HR images and super-resolved to 6x and 12x in the top 2 and bottom 2 rows respectively demonstrating out-of-scale performance. All models were trained for 1x-4x only therefore we refer to 6x and 12x as *out-of-scale*. From the images we can see that LIIF has a smoothing effect where it blurs out the high-level detail in the images. Comparatively, our models clearly produce sharper results retaining textural details like waves of water, texture in butterfly wings and fine hair of animals.

**Qualitative Analysis**

**Out-of-Scale**: The qualitative results on DIV2K validation set and Set14 test set are shown in Figure. 2 and Figure. 3 respectively. The proposed CiSR-GAN produces realistic images containing textures due to the adversarial and perceptual nature of the objective as compared to the LIIF \[8\]. LIIF’s output is always blurry for *out-of-scale* super-resolution smoothing out
Figure 3: Out-of-Scale Qualitative Comparison on Set 14: This figure shows the high resolution ground truth image (HR), the low-resolution image (LR), super-resolved image using LIIF model [8] and our model’s output (CiSR-GAN’s). All input images are 6x down-sampled from ground-truth images and super-resolved to 6x. All models were trained for 1x-4x only. We observe the same smoothing effect for LIIF outputs where the high level details such as water waves and texture in the fence has been blurred, while our model retains the high-level details and the image produced is much more realistic than LIIF.

Quantitative Results

CiSR-GAN vs LIIF We compare our model (CiSR-GAN) with previous work on the DIV2k dataset, as shown in Table. 1. The perceptual similarity metric (LPIPS) is a distance metric; therefore, the lower the value, the better. Whereas the higher the peak signal-to-noise ratio (PSNR), the better. Blau et al. [6] have previously shown that there is a trade-off between distortion and perception, and this can also be observed for our model. CiSR-GAN formulation has lower PSNR values than local implicit image function LIIF [8] as it is trained on the adversarial and perceptual loss. However, it consistently performs better than LIIF in terms of LPIPS metric. Lower LPIPS means that we can expect aesthetically pleasing results from CiSR-GAN. CiSR-GAN can also be evaluated for out-of-scale models easily since it is based on an INN. It maintains the edge over LIIF in terms of perceptual metrics for all scales evaluated.

In-Scale: We further compare the performance with state-of-the-art methods, including SRGAN, ESRGAN, and SPSR [23, 27, 20]. We notice that CiSR-GAN outperforms all in LPIPS while main-
| Method          | Metric | In-Scale | Out-of-Scale |
|-----------------|--------|----------|--------------|
|                 |        | ×2       | ×3           | ×4 | ×6       | ×12  | ×24  | ×30  |
| RDN-LHI [8]     | PSNR   | 34.99    | 31.26        | 29.27 | 26.99    | 23.89 | 21.31 | 20.59 |
|                 | LPIPS  | 0.0558   | 0.1344       | 0.1947 | 0.2760   | 0.4163 | 0.5506 | 0.5845 |
| CiSR-GAN (ours) | PSNR   | 32.01    | 27.95        | 26.30 | 24.27    | 21.67  | 19.52 | 18.92 |
|                 | LPIPS  | 0.0254   | 0.0641       | 0.1016 | 0.1642   | 0.3409 | 0.4839 | 0.5319 |

Table 1: Distortion vs Perception. Scaling factor for training is in range ×1–×4. Best values are bold.

| Dataset | Metric | SFTGAN [36] | SRGAN [20] | ESRGAN [37] | SPSR [23] | CiSR-GAN (ours) |
|---------|--------|-------------|------------|-------------|-----------|-----------------|
| Set5    | LPIPS  | 0.0890      | 0.0882     | 0.0748      | 0.0644    | 0.0604          |
|         | PSNR   | 29.932      | 29.168     | 30.454      | 30.400    | 30.05           |
| Set14   | LPIPS  | 0.4393      | 0.1663     | 0.1329      | 0.1318    | 0.1160          |
|         | PSNR   | 26.100      | 26.171     | 26.276      | 26.640    | 26.62           |
| B100    | LPIPS  | 0.5249      | 0.1980     | 0.1614      | 0.1611    | 0.1436          |
|         | PSNR   | 25.961      | 25.459     | 25.317      | 25.505    | 25.72           |
| Urban100| LPIPS  | 0.4726      | 0.1551     | 0.1229      | 0.1184    | 0.1179          |
|         | PSNR   | 23.145      | 24.397     | 24.360      | 24.799    | 24.36           |

Table 2: In-Scale Quantitative comparison with CNNs on benchmark datasets. This table shows CiSR-GAN with other perceptual quality focused methods. Best results are in bold. All models have been trained and tested on 4x down-sampled images.

5 Conclusion

In this work, we improved the perceptual quality of the implicit neural network based single image super-resolution. The main hindrance in utilizing adversarial losses for continuous image representation models was the random coordinate-based sampling procedure adopted by previous works. We proposed to use a patch-based sampling method. Then we trained the implicit neural network with additional objectives based on adversarial and perceptual losses. We demonstrated that the resulting network produces sharp and photorealistic images while maintaining the desirable properties of the implicit neural networks i.e out-of-scale super-resolution. As future work, our method can also be trained with gradient guidance based structure prior to improve PSNR.
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