OUR-GAN: One-shot Ultra-high-Resolution Generative Adversarial Networks

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ABSTRACT
We propose OUR-GAN, the first one-shot ultra-high-resolution (UHR) image synthesis framework that generates non-repetitive images with 4K or higher resolution from a single training image. OUR-GAN generates a visually coherent image at low resolution and then gradually increases the resolution by super-resolution. Since OUR-GAN learns from a real UHR image, it can synthesize large-scale shapes with fine details while maintaining long-range coherence, which is difficult with conventional generative models that generate large images based on the patch distribution learned from relatively small images. OUR-GAN applies seamless subregion-wise super-resolution that synthesizes 4k or higher UHR images with limited memory, preventing discontinuity at the boundary. Additionally, OUR-GAN improves visual coherence maintaining diversity by adding vertical positional embeddings to the feature maps. In experiments on the ST4K and RAISE datasets, OUR-GAN exhibited improved fidelity, visual coherency, and diversity compared with existing methods. The synthesized images are presented at https://anonymous-62348.github.io.

Figure 1: 8,192x4,320 UHR image synthesized by OUR-GAN. OUR-GAN can synthesize diverse high-fidelity UHR images over 8k from a single training image. We conducted training and synthesis on a single Titan RTX GPU.
1 Introduction

Recently, the demand for ultra-high-resolution (UHR) images with 4k or higher resolutions has increased. This paper proposes a framework one-shot ultra-high-resolution generative adversarial networks (OUR-GAN) that can synthesize a variety of high-quality UHR images from a single training image. Recently developed GAN models synthesize high-quality images by applying a variety of techniques such as the progressive growing approach, a hierarchy of multi-scale generators and discriminators, and auxiliary losses [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]. However, the output resolution of most generative models is limited to 1K (1024x1024).

Since a 4K UHD image consists of eight times more pixels than a 1K image, the UHR image synthesis model should synthesize substantially more information. To generate a UHR image with limited GPU memory, the model should synthesize images subregion by subregion and then concatenate them into a full-size image. However, it is difficult to maintain the visual coherence of global shape, the fidelity of detail, and shape diversity while synthesizing UHR images by subregion.

There are only a few previous studies on non-repetitive UHR image synthesis with a limited amount of GPU memory [11, 12, 13]. They synthesize images of arbitrary size by concatenating patterns learned from small images. However, it is hard to generate images containing shapes larger than those of the training images in such a way, as shown in Fig. 2. In addition, they require numerous training samples, but collecting a large number of UHR images is costly and impossible in certain application fields. A few recently developed generative models are trainable with a single training image [8, 9, 14, 10, 15]. They generate diverse images with similar content and style to the training image using internal patch distribution learned from a single image. However, they cannot generate images with a resolution greater than 1K, and there is room for improvement in visual coherence and diversity.

The proposed model, OUR-GAN, synthesizes non-repetitive high-fidelity UHR images with limited GPU memory and is trainable with a single training image, as shown in Fig. 1. Unlike existing models that generate UHR images by connecting small-scale patterns, OUR-GAN synthesizes diverse and visually coherent images at low resolution and then gradually increases the resolution by adding details via super-resolution. OUR-GAN synthesizes UHR images with limited GPU memory while preventing discontinuity at the boundary by a subregion-wise super-resolution. Since it learns directly from a real UHR image, it can generate large-scale shapes with fine details while maintaining long-range coherence. Additionally, we improved global shape coherence, maintaining diversity through vertical coordinate convolution. Up to our knowledge, OUR-GAN is the first non-repetitive UHR image synthesis model that is trainable with a single image.

The main contributions of our study include 1) the first framework to synthesize non-repetitive high-fidelity UHR images from a single training image, 2) a seamless subregion-wise super-resolution method that synthesizes UHR images with limited GPU memory, 3) applying vertical coordinate convolution for improving the coherence of the global shape while maintaining diversity, 4) a new 4K dataset for one-shot UHR image synthesis, and 5) improved experimental results on ST4K and RAISE datasets in terms of fidelity, visual consistency, and diversity compared to conventional methods.

Figure 2: 4K Image synthesized by InfinityGAN.
2 Related work

High-fidelity image synthesis Recently developed GANs apply the progressive growing approach to address the challenges in high-resolution image synthesis, such as training instability and image quality degradation \[1,2,3,4,5,6,7,8,9,10\]. They also apply various techniques to improve fidelity. StackGAN [5], StackGAN++ [6], and HDGAN [7] apply a hierarchy of multi-level generators and discriminators to learn feature distributions at various scales. LAPGAN [1], SinGAN [8], and ConSinGAN [9] apply the Laplacian pyramid framework that increases the resolution of the image by upsampling and complement details at each level. StyleGAN [3] and StyleGAN2 [4] synthesize high-resolution images by adjusting the ‘style’ at each scale while increasing the size of the feature maps. In addition, various methods such as minibatch discrimination [2], joint conditional-unconditional loss [6], matching pair loss [7], mixing regularization [3], and path length regularization [4] are employed to improve learning stability, image quality, and diversity.

Infinite-size image synthesis from small images UHR images composed of repeating textures can be easily created by connecting texture patches synthesized by existing methods [16, 17, 18]. However, such a method cannot synthesize complex and realistic images. There are few previous studies on non-repetitive UHR image synthesis. They synthesize images piece by piece and combine them to produce the full-size image. They use latent vectors to maintain the visual coherence of the global shape. InfinityGAN [12] maintains visual coherence by referencing a shared global latent while synthesizing each subregion. ALIS [11] synthesizes partial images globally coherent with one another by sharing latent anchor codes at regular distances in the coordinate system. To synthesize image parts, ALIS interpolates the anchor codes by spatially aligned adaptive instance normalization. Taming Transformer [13] creates latent code maps in an autoregressive manner and then synthesizes subregion images conditioned on the latent codes at the corresponding coordinates.

These models can synthesize images of arbitrary size without large-scale images. However, because they do not learn from real UHR images, they cannot catch large-scale shapes with fine details and long-range coherence. As well, they require a large number of samples for training.

Image synthesis from single training image In general, GAN models that can be trained from a single image learn the internal patch distribution of the training image and then synthesize new images based on the patch distribution [14, 8, 9, 10, 15]. InGAN [14] is the first GAN model that learns natural images from a single training image. The generator of InGAN learns the patch distribution at multiple scales guided by a multi-scale patch discriminator and a cycle-consistent loss. In synthesis, it generates images of different sizes and shapes while having the same patch distribution as the training image. SinGAN [8] learns the distribution of patches at multiple scales by a hierarchy of multi-level generators and discriminators. SinGAN prevents overfitting by applying the Laplacian pyramid framework (LAPGAN) [1] and training each generator one at a time, freezing the previous generators. HP-VAE-GAN [10] overcomes the mode collapse problem of GAN-based models and improves diversity by integrating PatchVAE [19] with GAN. SIV-GAN [15] improves global shape coherence and reduces overfitting by discriminating the image in the content and layout branches separately. However, the above models only synthesize images with a resolution of less than 1K. They also have room for improvement in terms of global shape coherence and shape diversity.

3 One-shot Ultra-high-resolution Generative Adversarial Networks

3.1 OUR-GAN Framework

OUR-GAN synthesizes UHR images with limited GPU memory through three steps, as shown in Fig. 3. First, OUR-GAN generates global structures at low resolution. Then, it increases the resolution as high as possible within the memory limit through in-memory super-resolution. Finally, it synthesizes a UHR image by further increasing the resolution beyond the memory limit by applying super-resolution subregion by subregion. The output resolution of the super-resolution model is limited to the resolution of the training image. However, ZSSR [20] and MZSR [21] have demonstrated that a super-resolution model can produce images 2 to 4 times larger than the training image by exploiting the internal recurrence of information. As well, our demo page presents 16K images (16,384x10,912) synthesized by OUR-GAN trained with an 8K (8,192 x 5,456) image.

3.2 Global structure generation

Learning to synthesize diverse images with globally coherent shapes from a single training image is challenging. In a preliminary experiment, we compared multiple models that can be trained with a single image. Among them, HP-VAE-GAN [10] exhibited higher diversity than other models but inadequate global coherence. Therefore, we selected HP-VAE-GAN as our baseline model for the first step and improved global coherence by applying vertical
Figure 3: UHR image synthesis by OUR-GAN. OUR-GAN synthesizes UHR images in three steps. 1) Global structure generation: The model creates low-resolution global structures and objects from random noises. 2) In-memory super-resolution: The super-resolution model up-scales the synthesized image to the maximum resolution within the available GPU memory. 3) Seamless subregion-wise super-resolution: If the super-resolution model can’t up-scale the entire image as input due to lack of GPU memory, the model up-scales the image subregion by subregion using the overlap-tile strategy.

coordinate convolution. HP-VAE-GAN synthesizes images through a hierarchical patch-based generation scheme as Eq. (1)-(3), where $G_m, \tilde{x}_m^1$ and $z_m^1$ denote the generator, synthesized image, and Gaussian noise vector at scale $m$, respectively. The symbol $\uparrow$ represents upsampling.

$$\tilde{x}_m^1 = \begin{cases} G_0^1(z_0^1) & \text{1} \leq m \leq L \text{ (1)} \\ \uparrow \tilde{x}_{m-1}^1 + G_m^1(\uparrow \tilde{x}_{m-1}^1) & \text{1} \leq m \leq L \text{ (2)} \\ \uparrow \tilde{x}_{m-1}^1 + G_m^1(\uparrow \tilde{x}_{m-1}^1 + z_m^1) & L < m \leq M \text{ (3)} \end{cases}$$

First, HP-VAE-GAN generates an initial image from Gaussian noise $z_0^1$, as Eq. (1), and then gradually increases the resolution as Eq. (2) and (3). In the early stages of $1 \leq m \leq L$, HP-VAE-GAN applies patch VAE [19], as Eq. (2), for diversity because the diversity of GAN models is limited due to the mode collapse problem. However, in the late stages of $L < m \leq M$, it applies patch GAN [22], as Eq. (3), for the fidelity of details.

The vertical coordinates of the visual components in the scenery have a strong bias [23]. Changes in the vertical position of components in the landscape image can result in visually incoherent or unreasonable layout, such as the sky below a mountain, whereas changes in the horizontal position do not cause serious problems. We exploit the spatial bias to prevent visually incoherent images.

The coordinate convolution [24] explicitly utilizes position information by concatenating coordinate channels to the input feature maps. However, when the model learns from a single image, applying the coordinate convolution as it is causes severe loss of diversity because the visual components correlates too strongly with absolute coordinates. Therefore, we concatenate only the vertical coordinate, not the horizontal coordinate, as Fig. 4 to attenuate the correlation between visual components and their location, thereby allowing for a variety of layouts. The vertical coordinate map contains the vertical coordinates of each location normalized to range from -1 to 1. In OUR-GAN, we replaced all convolution layers in the first step with the vertical coordinate convolutional layers. Previous work [24] also utilizes vertical coordinates to obtain attention value, but their method differs from ours significantly.
3.3 In-memory and subregion-wise super-resolution

In the second and third steps, OUR-GAN focuses on fidelity and increases the resolution of the previously synthesized images by adding in fine detail. In the third step, OUR-GAN applies subregion-wise super-resolution to increase the image resolution beyond the memory limit. The greatest technical challenge in these steps is learning the super-resolution model with a single training image. In this work, we achieved high fidelity by pre-training ESRGAN [25], a super-resolution model well-known for decent output quality, and then fine-tuning it with a single training image. In previous work, there were super-resolution models, such as ZSSR [20] and MZSR [21], that can learn from a single image. However, in our preliminary experiment, the pre-trained ESRGAN exhibited higher image quality than the zero-shot super-resolution modules. We used DIV2K [26] and Flickr2K [27] datasets to pre-train ESRGAN.

In the second step, we add random noise $z_{20}$ to the previously synthesized image $\tilde{x}_{1M}$, then increase the resolution by super-resolution model $G_{20}$ as $\tilde{x}_{20} = G_{20}(\tilde{x}_{1M} + z_{20})$. In the third step, we divide the image into subregions, apply super-resolution to each of the subregion images, and then concatenate the up-scaled subregions images into a single image of higher resolution, as shown in Fig. 5. Such a subregion-wise super-resolution can be repeated multiple times to produce UHR images of 4K or even higher resolution.

However, without careful design, such a subregion-wise super-resolution can produce discontinuity at the boundary. In previous work, there are a few methods to prevent discontinuity. Previous work has shown that the primary cause of the discontinuity is the zero-padding around the input feature map and has proposed a few remedies [28][29][12]. [28] applied the overlap-tile strategy that expands the input subregion area to block the influence of the zero padding at the boundary. [12] removes zero-padding by carefully designing their network with alternating convolutions and transpose convolutions.
Since the latter requires redesigning the network, we applied the former with an improvement. [28] applied the overlap-tile strategy to up-sample feature maps in a segmentation model. To prevent discontinuity at the boundary, the overlap should be larger than the receptive field of the layer. The size of theoretical receptive field (TRF) linearly increases with the depth of the network, which is large for a deep CNN. However, [30] analyzed the effective receptive field (ERF) of deep neural networks and discovered that ERF is substantially smaller than TRF and increases with the square root of network depth. Inspired by [30], we set the overlap size to the radius of ERF, as shown in Fig. 6, which is significantly smaller than that of TRF. The experimental results in Fig. 7 suggests that an overlap equal to the ERF radius is sufficient to prevent discontinuity. Since the asymptotic approximation of ERF is $O(\sqrt{\text{depth}})$ whereas that of TRF is $O(\text{depth})$, the benefit of our method is not negligible.

We compared the results of subregion-wise super-resolution with no overlap and overlap by ERF radius. Fig. 7 displays the difference between the output images of subregion-wise super-resolution and those of ordinary super-resolution that up-scales the image as a whole. Fig. 7(a) shows that, without overlap, subregion-wise super-resolution produces significant difference at the boundaries of subregions. However, overlapping subregions attenuated the discrepancy.

### 4 Experiments

#### 4.1 Experimental settings

**Datasets and experimental environment** To test and evaluate OUR-GAN, we collected a new 4K image dataset, Scenery and Texture-4K (ST4K), consisting of high-quality 4K scenery and texture images. The ST4K dataset includes a total of 50 copyright-free images on the Internet, 25 for each category, with a minimum resolution of $4,096 \times 2,160$ pixels. ST4K includes diverse natural and urban scenery images containing multiple global and structural patterns as well as different texture images sharing local characteristics. For more details of ST4K, refer to Appendix B.
OUR-GAN: One-shot Ultra-high-Resolution Generative Adversarial Networks

Figure 8: Qualitative comparison of non-repetitive 4K Image Synthesis. OUR-GAN synthesized globally coherent structures, while InGAN generated distorted objects. SinGAN also generated globally coherent structural patterns, but OUR-GAN synthesized fine details better.

We only used 25 scenery images for quantitative analysis since OUR-GAN was designed to synthesize non-repetitive images, and there are many methods in previous work that are applicable for texture images. Instead, we added 50 more high-fidelity complex images with a resolution of 4K or above from the landscape and building categories from the RAISE dataset, which is a public image dataset primarily designed for the evaluation of digital forgery detection. To evaluate one-shot generative models, we trained a separate model for each training image. We conducted experiments using multiple GPUs but trained each model on a single GPU. Most of our GPUs are GTX-2080 or GTX-1080 with 8GB memory.

**Metrics** In experiments, we measured Single Image Fréchet Inception Distance (SIFID) [8] to quantify the quality of synthesized images and Learned Perceptual Image Patch Similarity (LPIPS) [31] to quantify the diversity of synthetic patterns as [15]. [8] measured SIFID from low-level features extracted from the early layer of the Inception [32] network, whereas [15] measured SIFID from mid-level features at the output of the convolution layer before the auxiliary classifier of the Inception network. We used both methods to measure the similarity in both local and global patterns. All results presented in this paper are averaged measurements over 50 generated samples, except for InGAN [14], which is a conditional model.

4.2 One-shot 4K non-repetitive image synthesis

We selected three baseline models that can synthesize non-repetitive high-resolution images and are learnable from a single image: InGAN [14], SinGAN [8], and Sin+PE that combines positional encoding with SinGAN [33]. InGAN [14] synthesizes images by taking the training image as input and up-scaling the image to maximum resolution through a geometric transformation layer. SinGAN [8] synthesizes images by generating low-resolution images first, then up-scaling them by super-resolution based on internal patch recurrence of the low-resolution image. Sin-PE [33] adds Cartesian spatial grids to the input noise then synthesizes high-resolution images with SinGAN.

OUR-GAN synthesizes UHR images with 8GB GPU memory. However, the other one-shot models were not designed to synthesize UHR images with limited GPU memory. Since OUR-GAN is the first one-shot UHR image synthesis model, we were unable to find other models to compare fairly. Therefore, for the comparison with OUR-GAN, we trained the
Table 1: Quantitative results of 4K non-repetitive image synthesis. We measure SIFID at both 1K and 4K resolutions, extracting feature maps after the 5th and 13th convolutional layer of the Inception\[32\] Network. For simplicity, we count an Inception block as a single layer. ↓ indicates that the lower it is, the better.

| LAYER | ST4K  | RAISE |
|-------|-------|-------|
|       | 1K SIFID↓ | 4K SIFID↓ | 1K SIFID↓ | 4K SIFID↓ |
|       | 5TH | 13TH | 5TH | 13TH | 5TH | 13TH | 5TH | 13TH |
| InGAN | 8.34 | 7.21 | 14.46 | 6.04 | 7.50 | 8.13 | 12.63 | 5.94 |
| SinGAN | 3.07 | 4.93 | 6.38 | 3.79 | 3.19 | 6.31 | 5.21 | 4.01 |
| SIV+PE | 5.03 | 6.46 | 8.00 | 4.28 | 9.43 | 8.03 | 11.55 | 5.01 |
| OURs  | **0.85** | **2.83** | **1.36** | **1.48** | **0.73** | **3.30** | **1.22** | **1.50** |

Figure 9: Qualitative comparison in terms of global coherence and diversity. We train the framework replacing the model in the first step with baseline models: SinGAN [8], ConSinGAN [9], HP-V AE-GAN [10] and SIV-GAN [15]. OUR-GAN can synthesize visually coherent and diverse patterns, while other baseline models only generated almost identical images or produced visually distorted shapes.

 baseline models with downsampled training images, synthesized the image up to the maximum resolution possible for the baseline models, and then up-sampled the synthesized images to 4K resolution by bi-linear interpolation.

Fig. 8 displays the 4K samples generated by OUR-GAN and the baseline models as well as the ground truth image. InGAN [14] failed to synthesize visually plausible UHR images containing large-scale shapes because it synthesizes images by repeating small-sized patterns learned from small training samples. SinGAN can generate large-scale patterns but did not catch the fine details of the structure. However, OUR-GAN successfully synthesized high-quality images with visually coherent shapes with fine details. Compared with other models, OUR-GAN synthesized the most visually plausible images. OUR-GAN also outperformed other models in the quantitative study, as shown in Table 1. OUR-GAN scored the best SIFID in all configurations, which suggests that OUR-GAN synthesizes images with high-quality in both global shape and local details. More synthesized UHR image samples are presented in Appendix D.

4.3 Global coherence and diversity

To evaluate the effect of the vertical coordinate convolutions, we replaced the first step model of OUR-GAN with other models and compared the difference of the synthesized images: SinGAN [8], ConSinGAN [9], HP-V AE-GAN [10], and SIV-GAN [15]. For simplicity, we refer to the first-step model using vertical coordinate convolution as OUR-GAN in this subsection.

Fig. 9 displays the generated images. ConSinGAN and SIV-GAN generated patterns with limited diversity, while HP-V AE-GAN synthesized distorted structures that combine unrelated patterns. Compared to HP-V AE-GAN, OUR-GAN improves global coherence of patterns significantly, as shown in Fig. 10 and generates relatively more diverse patterns.
Figure 10: Effect of employing vertical coordinate convolution. OUR-GAN improves visual coherence by exploiting spatial bias with vertical coordinate convolution.

Table 2: Quantitative results of 4K non-repetitive image synthesis. We measure SIFID at 4K resolution according to the method calculated in Table 1 and LPIPS of all pairs of 50 synthesized images at 256p resolution. ↓ indicates that the lower the better while ↑ indicates the higher the better.

| Layer      | ST4K SIFID↓ | ST4K LPIPS↑ | RAISE SIFID↓ | RAISE LPIPS↑ |
|------------|-------------|-------------|--------------|--------------|
| SINGAN     | 1.54        | 1.67        | 1.50         | 1.77         |
| CONSinGAN  | 1.45        | 1.58        | 1.36         | 1.67         |
| HP-VAE-GAN | 1.47        | 1.56        | 0.42         | 1.34         |
| SIV-GAN    | 1.55        | 1.54        | 0.57         | 1.46         |
| OUR-GAN    | 1.36        | 1.48        | 0.30         | 1.22         |

Figure 11: 4K texture image synthesized by OUR-GAN. OUR-GAN can synthesize high-fidelity texture images.
compared to ConSinGAN and SIV-GAN. Table 2 presents the result of quantitative evaluation. OUR-GAN exhibited decent performance in quantitative results. OUR-GAN scored the lowest SIFID, which suggests that OUR-GAN is effective in learning the internal statistics of the training image. OUR-GAN did not show a significant difference compared with other baselines in LPIPS. However, high LPIPS does not always suggest the model produces high-quality images because it does not penalize visually incoherent patterns. Appendix H presents visually incoherent samples with high LPIPS. Although OUR-GAN lacks a little diversity compared to HP-VAE-GAN, OUR-GAN can synthesize more visually coherent images.

4.4 One-shot high-fidelity 4K texture image synthesis

We also evaluated the performance of OUR-GAN to synthesize high-fidelity UHR texture images. OUR-GAN learned from texture images in ST4K and synthesized UHR images. Fig. 11 displays two synthesized samples. OUR-GAN synthesized high-fidelity UHR texture images. More samples are presented on our demo page.

5 Conclusion

In this paper, we proposed the first One-shot Ultra-high-Resolution GAN framework (OUR-GAN) that synthesizes high-fidelity non-repetitive UHR images with a resolution of 4K or above and is learnable from a single image. OUR-GAN generates diverse and globally coherent large-scale shapes with fine details and maintains long-range coherence. We improved visual coherence by applying vertical coordinate convolution. With limited GPU memory, OUR-GAN can generate seamless UHR images with marginal overhead through the overlap-tile strategy combined with the proposed overlap estimation method.
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Appendix

A Implementation of the baseline models

We implemented the baseline models with open sources. These are the links to the open sources we employed.

- SinGAN: https://github.com/tamarott/SiGAN
- ConSinGAN: https://github.com/tohinz/ConSinGAN
- HP-VAE-GAN: https://github.com/shirgur/hp-vaegan
- Sin+PE: https://github.com/open-mmlab/mmgeneration
- InGAN: https://github.com/Caenorst/InGAN/tree/py3

Note that we implemented SIV-GAN with codes from the author, which have not been released.
B  ST4K dataset

We collected 4K or higher from Pixabay\footnote{https://pixabay.com/}. About scenery and texture categories, we tried to gather diverse images. To equalize the image size, we resized the images larger than 4K resolution to 4K. Fig. 12 and Fig. 13 shows all images of ST4K.

![Scenery images of ST4K](image_url)

Figure 12: Scenery images of ST4K.
Figure 13: Texture images of ST4K.
C Images chosen from RAISE

Figure 14: 50 images chosen from RAISE
D More qualitative results

Figure 15: 4K Image synthesized by OUR-GAN.
Figure 16: Another 4K Image synthesized by OUR-GAN.
Figure 17: Diverse images synthesized by OUR-GAN
Figure 18: Another diverse images synthesized by OUR-GAN
E Training

E.1 Training in the first step

We present the training procedure and algorithm in Fig. 19 and Algorithm 1. We compute the reconstruction loss $\mathcal{L}_{\text{recon}}$ with MSE, the adversarial loss $\mathcal{L}_{\text{adv}}$ with WGAN-GP loss [34], and the KL loss $\mathcal{L}_{\text{KL}}$ following [19].

![Training procedure in the 1st step.](image)

Figure 19: Training procedure in the 1st step.
Algorithm 1 Training algorithm in the 1st step.

Single training image at scale $m$: $x_m$
Total number of scales: $M$
The last scale applying patch VAE: $L$
Encoder: $E$
Generator at scale $m$: $G_m$
Discriminator at scale $m$: $D_m$
Random noise at scale $m$: $z_m$

for $m = 0$ to $M$ do
  for $i = 0$ to number of epochs do
    if $m = 0$ then
      $f \leftarrow E(x_0)$
      Samples latent codes $z_0$ with $f$
      $\tilde{x}_0 \leftarrow G_0(z_0)$
    end if
    if $1 \leq m \leq L$ then
      $\tilde{x}_m \leftarrow \uparrow \tilde{x}_{m-1} + G_m(\uparrow \tilde{x}_{m-1})$
    end if
    if $L < m \leq M$ then
      $\tilde{x}_m \leftarrow \uparrow \tilde{x}_{m-1} + G_m(\uparrow \tilde{x}_{m-1} + z_n)$
      $\text{real/fake} \leftarrow D_m(\tilde{x}_n), D_m(x_m)$
    end if
    if $m = 0$ then
      $\mathcal{L} \leftarrow \mathcal{L}_{\text{recon}}(\tilde{x}_0, x_0) + \beta_{\text{vae}} \mathcal{L}_{\text{KL}}(x_0)$
      Backpropagate $\mathcal{L}$
      Update $E$ and $G_0$
    end if
    if $1 \leq m \leq L$ then
      $\mathcal{L} \leftarrow \mathcal{L}_{\text{recon}}(\tilde{x}_n, x_n) + \mathcal{L}_{\text{recon}}(\tilde{x}_0, x_0) + \beta_{\text{vae}} \mathcal{L}_{\text{KL}}(x_0)$
      Backpropagate $\mathcal{L}$
      Update $E, G_0$, and $G_m$
    end if
    if $L < m \leq M$ then
      $\mathcal{L} \leftarrow \mathcal{L}_{\text{recon}}(\tilde{x}_n, x_n) + \beta_{\text{adv}} \mathcal{L}_{\text{adv}}(z, x_n)$
      Backpropagate $\mathcal{L}$
      Update $G_m$ and $D_m$
    end if
  end for
end for
E.2 Training in the second and third steps

We present the training procedure and algorithm in Fig. 20 and Algorithm 2. We first pretrain the super-resolution model (generator) with a large-scale dataset. Then, we fine-tune the super-resolution model (generator) with a single target image. We compute the reconstruction loss $L_{\text{recon}}$ with L1 distance, the adversarial loss $L_{\text{RaG}}^G$ and $L_{\text{RaG}}^D$ with RaGAN loss [35], and the perceptual loss $L_{\text{perceptual}}$ with the L1 distance between extracted features.

Figure 20: Training procedure in the 2nd and 3rd steps.
Algorithm 2 Pre-training algorithm in the 2nd and 3rd steps.

Dataset: $X = \{x^1, x^2, ..., x^n\}$
Generator: $G$
Discriminator: $D$
Feature extractor: $F$
Augmentation: $T$
Downsampling: $S$

for $i = 0$ to number of steps do
    Samples a mini-batch $x_{hr}$ from $X$
    $x_{lr} \leftarrow S(T(x_{hr}))$
    $x_{sr} \leftarrow G(x_{lr})$
    $\mathcal{L}_G \leftarrow \mathcal{L}_{recon}(x_{lr}, x_{sr})$
    Backpropagate $\mathcal{L}_G$
    Update $G$
end for

for $j = 0$ to number of steps do
    Samples a mini-batch $x_{hr}$ from $X$
    $x_{lr} \leftarrow S(T(x_{hr}))$
    $x_{sr} \leftarrow G(x_{lr})$
    $o_{sr}, o_{hr} \leftarrow D(x_{sr}), D(x_{hr})$
    $f_{sr}, f_{hr} \leftarrow F(x_{sr}), F(x_{hr})$
    $\mathcal{L}_G \leftarrow \mathcal{L}_{perceptual}(f_{lr}, f_{sr}) + \lambda \mathcal{L}_{Ra}^G(o_{sr}, o_{hr}) + \eta \mathcal{L}_{recon}(x_{lr}, x_{sr})$
    $\mathcal{L}_D \leftarrow \mathcal{L}_{Ra}^D(o_{sr}, o_{hr})$
    Backpropagate $\mathcal{L}_G$ and $\mathcal{L}_D$
    Update $G$ and $D$
end for
Algorithm 3 Fine-tuning algorithm in the 2nd and 3rd steps.

Dataset: $X = \{x^1, x^2, ..., x^n\}$
Generator: $G$
Discriminator: $D$
Feature extractor: $F$
Augmentation: $T$
Downsampling: $S$

Initialize $G$ with pre-trained weights.

for $i = 0$ to number of steps do
    Samples a mini-batch $x_{hr}$ from $X$

    $x_{lr} \leftarrow S(T(x_{hr}))$
    $x_{sr} \leftarrow G(x_{lr})$
    $o_{sr}, o_{hr} \leftarrow D(x_{sr}), D(x_{hr})$
    $f_{sr}, f_{hr} \leftarrow F(x_{sr}), F(x_{hr})$

    $\mathcal{L}_G \leftarrow \mathcal{L}_{\text{perceptual}}(f_{lr}, f_{sr}) + \lambda \mathcal{L}_G^{Ra}(o_{sr}, o_{hr}) + \eta \mathcal{L}_{\text{recon}}(x_{lr}, x_{sr})$
    $\mathcal{L}_D \leftarrow \mathcal{L}_D^{Ra}(o_{sr}, o_{hr})$

    Backpropagate $\mathcal{L}_G$ and $\mathcal{L}_D$
    Update $G$ and $D$
end for
The detailed structures of the generators and discriminators

Figure 21: The detailed structure of the first step model

Figure 22: The detailed structure of the second and third step models. We omitted activation functions for simplicity.
## G Hyperparameters

Table 3: Model hyperparameters in the first step.

| Hyperparameters | Value |
|-----------------|-------|
| # of iteration per scale | 5000 |
| # of intermediate layers | 5 |
| # of channels | 64 |
| GT size | 256 |
| kernel size | 3 |
| stride | 1 |
| padding size | 1 |
| type | Adam |
| betas | (0.5, 0.999) |
| learning rate | 0.0005 |
| gradient clip | 5 |
| weight of reconstruction loss | 10 |
| weight of KL loss | 1 |
| weight of discriminator loss | 1 |
| # of blocks | 2 |
| # of Patch-VAE | 3 |
| # of Patch-GAN | 6 |
| Scale factor | 0.75 |

Table 4: Model hyperparameters in the second and third steps.

| Hyperparameters | 2nd and 3rd step |
|-----------------|------------------|
| total iteration | 100,000 |
| # of channels | 64 |
| GT size | 128 |
| type | Adam |
| betas | (0.9, 0.999) |
| learning rate | 0.0001 |
| scheduling intervals | 30k, 60k, 90k |
| scheduling ratio | 0.5 |
| weight of perceptual loss | 1.0 |
| weight of reconstruction loss | 0.01 |
| weight of adversarial loss | 0.005 |
| # of RRDB blocks | 23 |
| upsampling ratio | 4 |
| standard deviation of random noise | 0.1 |
A limitation of LPIPS as a diversity metric.

Figure 23: A limitation of LPIPS as a diversity metric. We measured the LPIPS between the two synthesized images. HP-VAE-GAN synthesizes visually incoherent patterns, but the resulting images have a high LPIPS. A high LPIPS does not guarantee the desired diversity since it does not consider the visual coherence of patterns.