Efficient High-Resolution Image-to-Image Translation using Multi-Scale Gradient U-Net

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Abstract. Recently, Conditional Generative Adversarial Network (Conditional GAN) have shown very promising performance in several image-to-image translation applications. However, the uses of these conditional GANs are quite limited to low-resolution images, such as 256 × 256. The Pix2Pix-HD is a recent attempt to utilize the conditional GAN for high-resolution image synthesis. In this paper, we propose a Multi-Scale Gradient based U-Net (MSG U-Net) model for high-resolution image-to-image translation up to 2048 × 1024 resolution. The proposed model is trained by allowing the flow of gradients from multiple-discriminators to a single generator at multiple scales. The proposed MSG U-Net architecture leads to photo-realistic high-resolution image-to-image translation. Moreover, the proposed model is computationally efficient as compared to the Pix2Pix-HD with an improvement in the inference time nearly by 2.5 times. We provide the code of MSG U-Net model at https://github.com/laxmaniron/MSG-U-Net.

Keywords: Multi-Scale Gradient U-Net · Multiple Scales · Conditional GANs · Pix2Pix-HD · Image-to-Image Translation

1 Introduction

Recently, image-to-image translation has gained huge popularity after the success of Generative Adversarial Networks (GANs) [5] in a wide range of image processing and computer vision applications [1, 12, 2, 10]. In image-to-image translation, an image in a domain is generally transformed into the corresponding image in some other domain, such as translating semantically segmented label images into RGB images, aerial photos to maps, sketches to real faces, and indoor segmented images to real images.

In 2014, GAN was proposed by Goodfellow et al. [5] to synthesize photorealistic images with the help of generator and discriminator networks. In 2017, the GAN was extended for image-to-image translation in form of conditional GAN (i.e., Pix2Pix model) [6] which became very popular. Motivated from the conditional GAN, several variants of GANs have been developed for image-to-image translation [19, 11, 4]. However, these GAN models are generally not
designed for the high-resolution image-to-image translations. Moreover, these models can only produce images of good quality up to $256 \times 256$ resolution.

To improve the quality of generated images, Perceptual Adversarial Networks (PAN) for Image-to-Image Transformation [16] were proposed which uses perceptual losses from pre-trained image classification networks such as VGG-19 [14]. However, its output resolution is also limited to $256 \times 256$. In an another attempt, a progressive GAN [8] is proposed to train the generator and discriminator networks with first low-resolution images then high-resolution images, which poses an additional burden on the training. In 2018, Ting-Chun Wang et al. [17] proposed the Pix2Pix-HD model for high-resolution image synthesis and semantic manipulation with the help of conditional GANs. The Pix2Pix-HD [17] performs well for high-resolution image-to-image translation (up to $2048 \times 1024$) as well. However, it is computational resource hungry (the complexity of Pix2Pix-HD is about 3.32 TeraFlops) and requires huge memory (at least 8GB of GPU VRAM) even during the inference time. Recently, multi-scale gradient for GAN (MSG-GAN) [7] is introduced for the high-resolution image generation by utilizing the gradient information at different scales. However, the power of multi-scale gradient is not yet utilized for the image-to-image translation. In this paper, we tackle these issues of high-resolution image-to-image translation with the help of the proposed efficient Multi-scale Gradient U-Net inspired from MSG-GAN [7] which requires significantly less computational resources and generates the high-quality images.

Following are the main contributions of this paper:

- We propose a novel Multi-Scale Gradient U-Net (MSG U-Net) based GAN model for high-resolution image-to-image translation (up to $2048 \times 1024$) which is inspired from the MSG-GAN [7] architecture.
- The proposed MSG U-Net is very efficient as compared to the state-of-the-art GANs for high-resolution image-to-image translation. MSG U-Net requires half the memory (4GB of GPU VRAM) and computational resources (the complexity of MSG U-Net is about 1.28 TeraFlops) during inference time as compared to Pix2Pix-HD [17] while retaining the same level of details in the output images.

2 Proposed MSG U-Net GAN Model

In this section, we present the generator and discriminator architectures along with the objective function of the proposed MSG U-Net model.

2.1 Generator Architecture

MSG-GANs [7] generate high-resolution images up to $1024 \times 1024$ from latent vectors. It avoids the vanishing gradient problem faced by very deep networks by allowing the flow of gradients from the discriminator to the generator at multiple scales. Inspired by this work, we propose a new generator architecture
Fig. 1: The above figure shows the Network architecture of our proposed Multi-Scale Gradient U-Net (MSG U-Net) GAN model. The input from the source domain is provided to the network at various resolutions ranging from $128 \times 64$ to $2048 \times 1024$. Similarly, the generator network generates the output images in the target domain at various resolutions ranging from $128 \times 64$ to $2048 \times 1024$. The output image generated at a particular resolution is concatenated with the input image from the source domain at the same resolution and fed into the corresponding discriminator similar to Pix2Pix Conditional GAN [6]. The network uses multiple discriminators, i.e., one discriminator for each resolution.

Encoder Part of MSG U-Net Let the input image from the source domain be of resolution $2048 \times 1024$ fed to the encoder part of the network. The input image is passed through two convolutional blocks of kernel size $4 \times 4$ and stride 1. Each convolutional block consists of Convolution-BatchNorm-LeakyReLu layers. Then the resolution is reduced to $1024 \times 512$ by using a convolutional block of kernel size $4 \times 4$ with stride as 2. Then the output of the convolutional block is concatenated with the resized source image ($1024 \times 512$), passed through a convolutional block having kernel size $1 \times 1$. In this way, we form the encoder part of the generator by providing input from the source domain at various scales from $2048 \times 1024$ to $128 \times 64$. After $128 \times 64$ input block, the encoder follows normal U-net architecture, and the resolution of convolutional block is reduced to $8 \times 4$. Providing input at different scales at different stages to the encoder leads to the learning of important features such as overall shape information from the low-resolution and detailed texture information from the high-resolution image.
Decoder Part of MSG U-Net  The output of the encoder from the $8 \times 4$ convolutional block is considered as the input to the decoder. First, the decoder upsamples to $8 \times 16$ using the transposed convolution block (TransposedConvolution-BatchNorm-LeakyRelu). The $8 \times 16$ output from the transposed convolutional block is added to the output from the corresponding $8 \times 16$ encoder block using skip connections followed by a convolutional block with stride 1. In this manner, the decoder upsamples up to $2048 \times 1024$ using transposed convolutional blocks. In addition to this, the decoder has branching at different layers to generate output images in the target domain from $128 \times 64$ to $2048 \times 1024$ resolutions simultaneously.

The process of generating outputs at intermediate layers in the generator network is inspired from MSG-GANs [7] and GoogLeNet [15]. It helps the network to alleviate the problem of vanishing gradients. As the discriminators not only take generator’s final output as input but also the intermediate outputs, the gradients can flow from discriminators to the intermediate layers of the generator directly. This increases the stability during training and solves the problem of vanishing gradients when the U-Net architecture is very deep.

To illustrate the impact of having output of different resolutions at intermediate layers, we train the MSG U-Net with and without the intermediate output images for 20 epochs and show the gradient distribution in Fig. 2. It can be noticed that the gradients are very close to zero due to the gradient diminishing problem when output at intermediate layers are not used. Whereas the gradient is distributed better when the output at intermediate layers are used.

2.2 Discriminator Architecture

We use a modified version of multi-scale discriminators proposed in [17] while training. As our generator produces target images at different scales, we scale the source image to various scales and concatenate with generated output at corresponding scale and feed it to the discriminator as a fake sample(0). We also concatenate the source and actual target image at corresponding scale and feed
it to discriminator as a real sample(1). Images at different resolutions are fed into different discriminators. However, the architecture of discriminator is same at all scales. We use the same patch discriminator as used in Pix2Pix [6]. We found that multiple discriminators lead to better stability during training than using single discriminator for all scales described in MSG-GAN [7].

2.3 Loss Function

We use the improved adversarial loss proposed in Pix2Pix-HD [17] along with perceptual loss using VGG-19 [14] as our loss function for generator and all discriminators. Let $G$ be the generator and $D_1, D_2, ..., D_n$ be $n$ discriminators. Let $D_k^{(i)}(X, Y)$ be the output of the $i^{th}$ layer of discriminator $D_k$ when fed with input images $\{X, Y\}$. Let $E_i$ be the total no. of elements in the $i^{th}$ layer of discriminator and $P$ be total number of layers in discriminator. Consider $x_k$ as the source image and $y_k$ as the corresponding target image at resolution $k$ with $z_k$ as the corresponding generated output. For perceptual loss, assume $F_k$ as the pre-trained VGG-19 [14] with frozen weights handling inputs at resolution $k$, $U$ as the number of convolution layers in VGG-19 and $F_k^{(i)}(X)$ be the output of the $i^{th}$ layer of VGG-19 network $F_k$ when fed with input image $X$. Consider $V_i$ be the total no. of elements in $i^{th}$ layer of VGG-19. The final objective/loss
Table 1: The results comparison of the proposed MSG U-net with state-of-the-art image-to-image translation GANs on Cityscapes [3], NYU Indoor RGBD [9] and Aerial Images to Maps [6] datasets.

| Model                      | Cityscapes | NYU Indoor RGBD | Aerial Images to Maps |
|----------------------------|------------|-----------------|-----------------------|
|                            | PSNR  SSIM VIF | PSNR  SSIM VIF | PSNR  SSIM VIF        |
| Pix2Pix (256 × 256) [6]   | 15.74 0.42 0.05 | 18.08 0.45 0.07 | 26.20 0.64 0.02       |
| PAN (256 × 256) [16]      | 16.06 0.48 0.06 | 19.23 0.54 0.11 | 28.32 0.75 0.16       |
| Pix2Pix-HD (512 × 512) [17]| -        -       -         | 25.01 0.79 0.28 | 32.32 0.87 0.24       |
| Pix2Pix-HD (2048 × 1024) [17]| 22.18 0.66 0.14 | - - - | - - - |
| MSG U-Net (512 × 512)     | -        -       -         | 25.17 0.77 0.27 | 31.04 0.84 0.23       |
| MSG U-Net (2048 × 1024)   | 23.99 0.69 0.15 | - - - | - - - |

function $L_{total}$ of the proposed MSG U-Net model can be written as:

$$L_{total} = \max_{G} \min_{D_1, D_2, \ldots, D_n} \sum_{k=1}^{n} L_{GAN}(G, D_k) +$$

$$\alpha \sum_{k=1}^{n} \sum_{i=1}^{P} \frac{1}{E_i} \left[ \| D^{(i)}_k (x_k, y_k) - D^{(i)}_k (x_k, z_k) \|_1 \right]+$$

$$\beta \sum_{k=1}^{n} \sum_{i=1}^{U} \frac{1}{V_i} \left[ \| F^{(i)}_k (y_k) - F^{(i)}_k (z_k) \|_1 \right]$$

(1)

where $L_{GAN}$ denotes the adversarial loss and $\alpha$ and $\beta$ are multiplication factor for feature loss [17] and perceptual loss [16], respectively.

3 Experiments and Results

We provide a comprehensive quantitative comparison against state-of-the-art methods over three datasets. In all the experiments, we set the hyper-parameters $\alpha$ and $\beta$ described in equation (1) to 10 and 0.25, respectively, based on the extensive hyper-parameter tuning. We use Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM) [18], and Visual Information Fidelity (VIF) [13] as the evaluation metrics. We compare our method with the state-of-the-art image-to-image translation GANs, including Pix2Pix [6], Perceptual Adversarial networks (PAN) [16], and Pix2Pix-HD [17].

We use three benchmark datasets, namely Cityscapes [3], NYU Indoor RGBD [9], and Aerial Images to Maps [6]. Cityscapes dataset consists of segmented RGB image of city streets in the source domain and corresponding photo-realistic image in the target domain at resolution 2048 × 1024. NYU Indoor RGBD dataset consists of segmented indoor images in the source domain and corresponding real images in the target domain at resolution 512 × 512. Aerial Images to Maps dataset consists of aerial photographs in the source domain and corresponding map of the image in the target domain at resolution 512 × 512.
### Table 2: Ablation study on Cityscapes dataset.

| Resolution  | Output Resolution | SSIM  |
|-------------|-------------------|-------|
| 128×64      | 256×128           | 0.42  |
| 256×128     | 512×256           | 0.56  |
| 512×256     | 1024×512          | 0.59  |
| 1024×512    | 2048×1024         | 0.63  |
| 2048×1024   |                   | 0.65  |

### Table 3: Ablation studies on NYU Indoor RGBD and Aerial Images to Maps datasets.

| Size  | Output over NYU Indoor RGBD dataset | Output over Aerial Images to Maps dataset |
|-------|-----------------------------------|------------------------------------------|
| 64    | 0.51 0.57 0.58 0.57               | 0.51 0.57 0.61 0.61                     |
| 128   | 0.69 0.75 0.76 0.72               | 0.64 0.78 0.79 0.78                     |
| 256   | 0.71 0.78 0.80 0.76               | 0.77 0.82 0.83 0.83                     |
| 512   | 0.71 0.79 0.80 0.77               | 0.79 0.84 0.86 0.84                     |

### 3.1 Quantitative Results

The experimental results in terms of the PSNR, SSIM and VIF are reported in Table 1 over Cityscapes, NYU Indoor RGBD, and Aerial Images to Maps datasets. Note that we remove the topmost input layer and the output layer of dimension 2048×1024 and resize the 1024×512 input and output resolution to 512×512 to facilitate the experiments on NYU Indoor RGBD and Aerial Images to Maps datasets. It is noticed from the results that the proposed MSG U-Net outperforms the Pix2Pix, PAN, and Pix2Pix-HD models over Cityscapes dataset. However, the results of the MSG U-Net is very close to Pix2Pix-HD over NYU Indoor RGBD and Aerial Images to Maps datasets. Note that Pix2Pix-HD is 2.5 times computationally more expensive than our MSG U-Net. Thus, the proposed model is very efficient as compared to the Pix2Pix-HD and generates the output images with similar quality.

### 3.2 Ablation Study

The proposed MSG U-Net takes an input from the source domain and down-sample it to various resolutions. In this experiment, we take the down-sampled input image such as 128×64 and again sample it to all input scales and feed it to generator. The purpose of this ablation study is to check the capability of MSG U-Net to perform both image-translation and super-resolution, simultaneously. We report SSIM under different input and output resolution settings in Table 2 over Cityscapes and Table 3 over NYU Indoor RGBD and Aerial Images to Maps datasets. It is observed that even if the resolution of input image is reduced
roughly by half, the results are not much degraded. In fact, the results are mostly comparable for different input resolutions. This can be quiet useful during the inference if high-resolution input images are not available, we can still generate high-resolution target images.

### 3.3 Qualitative Results

We present the images generated by the proposed MSG U-Net model in this section. To be precise Fig. 4 shows the source images, target images and generated images from Cityscapes dataset [3]. Fig. 5 shows results on NYU Indoor RGB-D dataset [9]. Fig. 6 shows results on Aerial Images to Maps dataset [6]. The quality of the generated images can be easily observed for the high-resolution synthesis in these results.

![Example results on Cityscapes dataset](image)

Fig. 4: Example results on Cityscapes dataset. Here, we convert segmented-RGB image to photo realistic image.
Fig. 5: Example results on NYU Indoor RGBD dataset images. Here, we convert segmented indoor images to photo realistic images.
Fig. 6: Example results on Aerial Images to Maps dataset images. Here, we convert aerial photographs to maps.
4 Conclusion

In this paper, we proposed a Multi-scale gradient based U-Net (MSG U-Net) for high-resolution image-to-image translation. The proposed model shows better training due to the utilization of the gradients at different scales. The proposed MSG U-Net (1.28 Tera-Flops) is computationally efficient as compared to Pix2Pix-HD (3.32 Tera-Flops). In spite of being an efficient model, the MSG U-Net has shown either better or comparable performance over three benchmark datasets. It is also observed that the MSG U-Net can produce high-quality output images even from the low-resolution input images.

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