Memory Efficient Patch-based Training for INR-based GANs

Namwoo Lee\textsuperscript{1,2*} Hyunsu Kim\textsuperscript{1} Gayoung Lee\textsuperscript{1} Sungjoo Yoo\textsuperscript{2} Yunjey Choi\textsuperscript{1}

\textsuperscript{1}NAVER AI Lab \quad \textsuperscript{2}Seoul National University

Abstract

Recent studies have shown remarkable progress in GANs based on implicit neural representation (INR) - an MLP that produces an RGB value given its (x, y) coordinate. They represent an image as a continuous version of the underlying 2D signal instead of a 2D array of pixels, which opens new horizons for GAN applications (e.g., zero-shot super-resolution, image outpainting). However, training existing approaches require a heavy computational cost proportional to the image resolution, since they compute an MLP operation for every (x, y) coordinate. To alleviate this issue, we propose a multi-stage patch-based training, a novel and scalable approach that can train INR-based GANs with a flexible computational cost regardless of the image resolution. Specifically, our method allows to generate and discriminate by patch to learn the local details of the image and learn global structural information by a novel reconstruction loss to enable efficient GAN training. We conduct experiments on several benchmark datasets to demonstrate that our approach enhances baseline models in GPU memory while maintaining FIDs at a reasonable level.

1. Introduction

Recent advances in Generative Adversarial Networks (GANs) \cite{8, 11, 12} enable realistic image synthesis and show practical and diverse applicability such as image-to-image translation \cite{5, 6, 10, 14, 16}, 3d-aware image generation \cite{4, 9, 19, 20}, real image editing \cite{1, 13, 26}, etc. Typical GANs view images as 2D pixel arrays and build them using convolutional filters. However, thanks to the success of NeRF in 3D modeling, it is also getting popular to view images as a continuous function in GANs. Implicit Neural Representations (INR) \cite{3, 7, 18, 21, 22, 25} is a popular method that use a neural network to approximate the continuous function. A number of recent studies including CIPS \cite{2} and INR-GAN \cite{23} have proposed a model that combines the INR concept and GANs. These INR-based GANs can naturally and easily do what was difficult in convolutional GANs, such as partial patch generation, zero-shot super-resolution, and image extrapolation.

Despite the advantages of INR-based GANs, it is difficult to train them because they are hardware intensive due to a lot of network inference proportional to the image size. Unlike convolutional GANs \cite{12, 17} which use upsampling and convolutional filters, pure INR-based GANs need to infer each coordinate of an image, so it consumes much more GPU memory. For example, CIPS requires 4 times more GPU memory than StyleGAN2. Therefore, reducing computation costs is an important research topic to practically use INR-based GANs. INR-GAN reduces the costs in the generator by factorizing the parameters and progressively growing the feature maps similar to StyleGAN2. However, their method is still computationally expensive because it starts with a feature map of large size \((64^2)\) and requires generating the entire image for the discriminator.

In this paper, we propose a method that can dramatically reduce the training costs for INR-based GAN using multi-stage patch-based training. During training, our method generates small patches \((32^2)\) instead of entire images, and the generated patches are fed to the discriminator. This patch-wise training can save a lot of GPU memory, but since the discriminator only sees the patches, it cannot give feedback on global structures. To solve this problem, we propose a novel multi-stage training method and progressively reduce the receptive field of each stage patch. Specifically, in the initial stage, the target patch is coarsely and globally sampled from an image, whereas in the final stage, the patch of equal size is densely and locally sampled. Then, in order to transfer the knowledge about the global structure of the previous stage to the current stage, we apply the consistency loss between the current generated patches and the patches cropped from the previously generated patches. By doing this, the final generator can generate a globally consistent image while it is trained using only local patches. We conduct extensive experiments with various datasets and show that our method reduces the required size of GPU memory and training time effectively while maintaining the quality of generated images comparable to the existing methods.

\textsuperscript{*}This work was done during an internship at NAVER AI Lab.
2. Multi-stage patch-based training

We propose multi-stage patch-based training, which reduces the computational cost for training INR-based GANs. We build upon the INR-based GAN [2] and keep every other component except the training strategy and patch regularization, including the adversarial loss, and hyperparameters. Overall framework can be shown in Figure 1.

For efficient training, we aim to generate local patches instead of full images (e.g., generating $64^2$ patches instead of creating $256^2$ images can reduce the computational cost such as GPU memory by $\frac{1}{4}$). However, it is known that the generator $G$ cannot learn the global structure of an image by providing only small patches to the discriminator [17]. To alleviate this problem, we adopt multi-stage training in which the generator learns to produce a coarse full image in the early stage of training (Stage 1 in Figure 1b) and learns to generate local patches with fine details in the later stages (Stage 2, 3 in Figure 1b).

Sparse-to-dense coordinate sampling. During training, we sample $(x, y)$ coordinates in a sparse-to-dense manner. We first define a set of integer pixel coordinates $\text{grid}$ as:

\[
\text{grid}(H, W, N) = \left\{ \left( \frac{H}{N}k, \frac{W}{N}k \right) \mid 0 \leq k < N \right\} \quad (1)
\]

where $H, W$ are the height and width of training image resolution, respectively (e.g., $256^2$), and $k$ is an integer value. A small $N$ gives sparsely sampled coordinates, while a large $N$ gives densely sampled ones. In the first stage of training, we set $N$ to $\frac{H}{4}$ to reduce the size of the coordinate grid to $\frac{1}{16}$ of its full resolution (sparse sampling). In the second and third stages of training, we set $N$ to $\frac{H}{2}$ and $H$, respectively (dense sampling). We apply appropriate random cropping to reduce the computational cost in the later stages.

Coarse-to-fine patch generation. We train the generators to produce coarse global images in the early stage of training and local patches with fine details in the later stages. Here, we denote the generator for each stage $i \in \{1, 2, 3\}$ as $G_i$, for clarity. Our generator $G_i$ takes as input a random Gaussian vector $z \in \mathbb{R}^{128}$ shared across all pixels and pixel coordinates $(x, y) \in \{0, \ldots, W-1\} \times \{0, \ldots, H-1\}$.

The first stage generator $G_1$ produces a coarse global image $I_1$ by performing an MLP operation for each $(x, y)$ coordinate, while keeping random vector $z$ fixed:

\[
I_1 = \{ G_1(x, y; z) \mid (x, y) \in \text{grid}(H, W, \frac{H}{4}) \}. \quad (2)
\]

We train $G_1$ with an adversarial loss [8] to generate images that are indistinguishable from real images of low resolution. Note that unlike traditional INR-based GANs [2, 23],...
where resize the later stage (i.e. trained in the previous stage to initialize the generator in local patches instead of full images. We use the generator the required size of GPU memory (30GB) instead of

In this section, we conduct experiments on various benchmark datasets (FFHQ, LSUN Church, and AFHQ) to verify the effectiveness of our method. All experiments are conducted at 256 × 256 scale with the G3 generator, and we use the Fréchet inception distance (FID) metric to show that our method still retains comparable performance in image generation.

3.1. Baseline Models

Since CIPS [2] is one of the state-of-the-art INR-based GANs, we demonstrate the applicability of our method to the CIPS model. To show the effectiveness of our method, we compare our method with three baselines. Image-based method is the original version of CIPS network. We do not change any configurations from its paper. Patch-based method is the patch-based training without our multi-stage training and patch regularization. The network is trained with 4× smaller patches and only adversarial loss term.

Gradient Accumulation is the same as Image-based method except for the batch size. To avoid the GPU memory limitation, some recent works [11, 12] may use small batch size and accumulate gradients. The network weights are updated once every multiple batches, whose summation is equal to that of the original batch size.

3.2. Main results

Figure 2 and Table 1 show the qualitative and quantitative results. For a fair comparison, we trained all baselines with the same training time; 4, 5, 6 days for AFHQ, FFHQ, and LSUN Church, respectively. We set the training time in proportion to the size of the data. Gradient Accumulation method is excluded from Table 1 because it needs n× more time if we want to use n× smaller batch size. Ours shows

Figure 2. Qualitative comparison with the baselines and our method. The first/second/third row shows samples from FFHQ/LSUN Church/AFHQ, respectively. The image-based model offers the best quality but requires much GPU memory (86GB), whereas the patch-based model needs much less GPU memory (30GB) but generates globally inconsistent images. Our method uses the comparable amount of GPU memory (31GB) to the patch-based model, while producing much better image quality.
visual comparable quality compared to the original CIPS network while it needs 2.8 x less memory of GPU. Without our multi-stage training, image quality deteriorates significantly in the patch-based method. Our method needs only 3% additional GPU memory but shows significantly better image generation quality than patch-based method according to the FID score; FIDs increase by 17.27, 8.40, and 22.26 in FFHQ, LSUN Church, and AFHQ, respectively. Since our method and the patch-based model generate only part of an image, each training iteration takes significantly less time than the image-based model, and we can run more training iterations in the same amount of time. Note that our method is slightly faster than the patch-based model because we can skip random cropping for the first stage.

### 3.3. Effect of patch regularization

In multi-stage patch-based training, we propose patch regularization which matches the generated patches of different training phases as we've discussed in Section 2. Figure 3 shows our regularization makes the network produce consistent structure in all stages. Stage 1 shows blurry but structurally meaningful images, and stage 3 shows high-fidelity images while maintaining the structure of the early stages. Without this loss term, our network cannot fully exploit the advantage of the multi-stage training.

### 3.4. Extrapolation Results

In Figure 4, we show the results of extrapolation on LSUN Church using our method. Thanks to the advantages of INR-based model, our method can generate an image of a size not seen during training by simply feeding the targeted coordinates.

### 4. Conclusion and Discussion

In this paper, we propose multi-stage patch-based training, a novel and scalable approach that can train INR-based GANs with a flexible computational cost regardless of the image resolution. We conducted experiments on several benchmark datasets and demonstrated that our method contributes to reducing the required size of GPU memory in training INR-based GAN models.

Our method also has some limitations. The proposed patch regularization might be too restrictive as it forces the patch generated in the current stage to be strongly match the image in the previous step. Also, the performance of multi-stage training for a specific dataset (i.e. FFHQ) could be more improved. Improving the performance and devising more flexible regularization to extract global structures would be one of the meaningful future work.

**Acknowledgements.** The authors thank NAVER AI Lab researchers for constructive discussion. All experiments were conducted on NAVER Smart Machine Learning (NSML) platform [15, 24].
References

[1] Rameen Abdal, Yipeng Qin, and Peter Wonka. Image2stylegan: How to embed images into the stylegan latent space? In CVPR, 2019. 1

[2] Ivan Anokhin, Kirill Demochkin, Taras Khakhulin, Gleb Sterkin, Victor Lempitsky, and Denis Korzhenkov. Image generators with conditionally-independent pixel synthesis. arXiv preprint arXiv:2011.13775, 2020. 1, 2, 3

[3] Matan Atzmon and Yaron Lipman. Sal: Sign agnostic learning of shapes from raw data. In CVPR, 2020. 1

[4] Eric R Chan, Marco Monteiro, Petr Kellnhofer, Jiajun Wu, and Gordon Wetzstein. pi-gan: Periodic implicit generative adversarial networks for 3d-aware image synthesis. In CVPR, 2021. 1

[5] Yunjey Choi, Minje Choi, Munyoung Kim, Jung-Woo Ha, Sunghun Kim, and Jaegul Choo. Stargan: Unified generative adversarial networks for multi-domain image-to-image translation. In CVPR, 2018. 1

[6] Yunjey Choi, Youngjung Uh, Jaejun Yoo, and Jung-Woo Ha. Stargan v2: Diverse image synthesis for multiple domains. In CVPR, 2020. 1

[7] Kyle Genova, Forrester Cole, Daniel Vlasic, Aaron Sarna, William T Freeman, and Thomas Funkhouser. Learning shape templates with structured implicit functions. In ICCV, 2019. 1

[8] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial networks. In NeurIPS, 2014. 1, 2

[9] Jiatao Gu, Lingjie Liu, Peng Wang, and Christian Theobalt. Stalegant: A style-based 3d-aware generator for high-resolution image synthesis. ICLR, 2022. 1

[10] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros. Image-to-image translation with conditional adversarial networks. In CVPR, 2017. 1

[11] Tero Karras, Samuli Laine, and Timo Aila. A style-based generator architecture for generative adversarial networks. In CVPR, 2019. 1, 3

[12] Tero Karras, Samuli Laine, Miika Aittala, Janne Hellsten, Jaakko Lehtinen, and Timo Aila. Analyzing and improving the image quality of stylegan. In CVPR, 2020. 1, 3

[13] Hyunsu Kim, Yunjey Choi, Junho Kim, Sungjoo Yoo, and Youngjung Uh. Exploiting spatial dimensions of latent in gan for real-time image editing. In CVPR, 2021. 1

[14] Hyunsu Kim, Ho Young Jhoo, Eunhyeok Park, and Sungjoo Yoo. Tag2pix: Line art colorization using text tag with secat and changing loss. In ICCV, 2019. 1

[15] Hanjoo Kim, Minkyu Kim, Dongjoo Seo, Jinwoong Kim, Heungseok Park, Soeun Park, Hyunwoo Jo, KyungHyun Kim, Youngil Yang, Youngkwon Kim, et al. Nsml: Meet the mlaas platform with a real-world case study. arXiv preprint arXiv:1810.09957, 2018. 4

[16] Junho Kim, Minjae Kim, Hyeonwoo Kang, and Kwang Hee Lee. U-gat-it: Unsupervised generative attentional networks with adaptive layer-instance normalization for image-to-image translation. In ICLR, 2020. 1

[17] Chieh Hubert Lin, Chia-Che Chang, Yu-Sheng Chen, Da-Cheng Juan, Wei Wei, and Hwann-Tzong Chen. COCOGAN: generation by parts via conditional coordinating. In ICCV, 2019. 1, 2

[18] Ben Mildenhall, Pratul P Srinivasan, Matthew Tancik, Jonathan T Barron, Ravi Ramamoorthi, and Ren Ng. Nerf: Representing scenes as neural radiance fields for view synthesis. In ECCV, 2020. 1

[19] Michael Niemeyer and Andreas Geiger. Giraffe: Representing scenes as compositional generative neural feature fields. In CVPR, 2021. 1

[20] Roy Or-El, Xuan Luo, Mengyi Shan, Eli Shechtman, Jeong Joon Park, and Ira Kemelmacher-Shlizerman. Stylesdf: High-resolution 3d-consistent image and geometry generation. 2022. 1

[21] Jeong Joon Park, Peter Florence, Julian Straub, Richard Newcombe, and Steven Lovegrove. Deepsd: Learning continuous signed distance functions for shape representation. In CVPR, 2019. 1

[22] Vincent Sitzmann, Julien Martel, Alexander Bergman, David Lindell, and Gordon Wetzstein. Implicit neural representations with periodic activation functions. 2020. 1

[23] Ivan Skorokhodov, Savva Ignatyev, and Mohamed Elhoseiny. Adversarial generation of continuous images. CVPR, 2020. 1, 2

[24] Nako Sung, Minkyu Kim, Hyunwoo Jo, Youngil Yang, Jingwoong Kim, Leonard Lausen, Youngkwon Kim, Gayoung Lee, Donghyun Kwak, Jung-Woo Ha, et al. Nsml: A machine learning platform that enables you to focus on your models. arXiv preprint arXiv:1712.05902, 2017. 4

[25] Sihyun Yu, Jihoon Tack, Sangwook Mo, Hyunsu Kim, Junho Kim, Jung-Woo Ha, and Jinwoo Shin. Generating videos with dynamics-aware implicit generative adversarial networks. 2022. 1

[26] Jiapeng Zhu, Yujun Shen, Deli Zhao, and Bolei Zhou. In-domain gan inversion for real image editing. In ECCV, 2020. 1