

GANeRF: Leveraging Discriminators to Optimize Neural Radiance Fields

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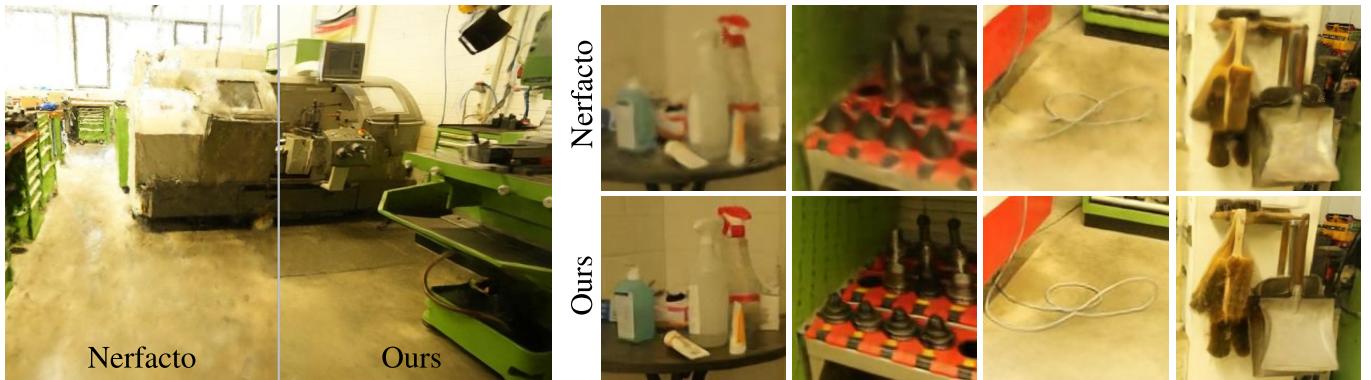


Fig. 1. GANeRF proposes an adversarial formulation whose gradients provide feedback for a 3D-consistent radiance field representation. This introduces additional constraints that enable more realistic renderings, and lead to improved novel view synthesis compared to Nerfacto and other baselines.

Neural Radiance Fields (NeRFs) have shown impressive novel view synthesis results; nonetheless, even thorough recordings yield imperfections in reconstructions, for instance due to poorly observed areas or minor lighting changes. Our goal is to mitigate these imperfections from various sources with a joint solution: we take advantage of the ability of generative adversarial networks (GANs) to produce realistic images and use them to enhance realism in 3D scene reconstruction with NeRFs. To this end, we learn the patch distribution of a scene using an adversarial discriminator, which provides feedback to the radiance field reconstruction, thus improving realism in a 3D-consistent fashion. Thereby, rendering artifacts are repaired directly in the underlying 3D representation by imposing multi-view path rendering constraints. In addition, we condition a generator with multi-resolution NeRF renderings which is adversarially trained to further improve rendering quality. We demonstrate that our approach significantly improves rendering quality, e.g., nearly halving LPIPS scores compared to Nerfacto while at the same time improving PSNR by 1.4dB on the advanced indoor scenes of Tanks and Temples.

CCS Concepts: • Computing methodologies → Reconstruction.

Additional Key Words and Phrases: Neural radiance fields, Novel view synthesis

1 INTRODUCTION

Neural Radiance Fields (NeRFs) [Mildenhall et al. 2020] can achieve remarkable novel view synthesis (NVS) results, powering applications in the domains of virtual/mixed reality, robotics, computational photography, and many others. Given a set of posed input images,

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NeRFs distill complex and viewpoint-dependent scene information, parameterized as 5D input vectors (3D coordinates + 2D viewing direction), into volumetric density and color fields modeled with a neural network. Volumetric rendering techniques are then applied to generate photorealistic 2D output images for novel camera views from these fields. While NeRFs are highly effective at providing compact scene representations that enable photorealistic NVS, their applicability is nonetheless still limited for in-the-wild use cases.

That is, NeRFs are optimized to overfit to the training dataset's appearance information, which makes them highly dependent on carefully collected input data and properly chosen regularization strategies. In fact, the shape-radiance ambiguity [Zhang et al. 2020] describes that a set of training images can be perfectly regenerated from a NeRF without respecting the underlying geometry, but by simply exploiting the view-dependent radiance to simulate the actual scene geometry. As a consequence, novel view synthesis quality for non-training camera views drastically degrades and the generated images exhibit well-known cloudy *floaters* artifacts. Unfortunately, even with significantly increased capture efforts and when input data comprises dense coverage for a scene, the reconstruction problem can remain ambiguous in areas with changing lighting conditions or in reflective or low-textured regions. Finally, for making NeRFs more widely adopted and applicable, the image capture process needs to be simple and of low effort while yielding high-quality reconstruction results.

In our work, we take advantage of generative adversarial networks (GANs) to improve the NeRF quality in challenging real-world scenarios. To this end, we introduce GANeRF – a novel approach for resolving imperfections directly in the NeRF reconstruction.

Our key idea is to leverage an adversarial loss formulation in an end-to-end fashion to introduce additional rendering constraints from a per-scene 2D discriminator. In particular, in regions with limited observations, this enforces the radiance field representation to generate patches that follow the distribution of real-world image patches more closely. Consequently, GANeRF enables notable mitigation of quality degradation effects in NVS due to imperfect input data, independently of their root causes like limited coverage, image distortion, or illumination changes.

We propose a joint adversarial training during the NeRF optimization, such that a 2D patch discriminator informs the NeRF about the degree of photorealism for rendered patches. Through gradient feedback into the 3D scene representation, we reduce typical imperfections in the radiance field reconstruction while inherently encouraging 3D-consistent, photorealistic NeRF renderings. We show how to further improve the output quality with a subsequent generator that operates on the 2D NeRF renderings at multiple scales, by refining them to provide closer matches to the real distribution of the scene’s images. We evaluate our method on challenging indoor scenes from the novel ScanNet++ [Yeshwanth et al. 2023] and the well-known Tanks and Temples [Knapitsch et al. 2017] datasets, and show that leveraging our adversarial formulation within NeRFs leads to significant image quality improvements over prior works. Across all test scenes, we obtain remarkable improvements over the best-performing baselines [Barron et al. 2022; Tancik et al. 2023] for perceptual metrics like LPIPS (reductions between 28-48%), while maintaining consistently better PSNR and SSIM scores.

In summary, we provide the following contributions:

- We introduce a novel adversarial formulation that imposes patch-based rendering constraints obtained from a 2D discriminator to optimize a 3D-consistent radiance field representation.
- We propose a 2D generator that further refines the rendering output, demonstrating significant improvements over state-of-the-art methods in novel view synthesis on challenging, large-scale scenes.

2 RELATED WORK

Neural Radiance Fields (NeRFs) model a 3D scene as a volumetric function, which can be rendered from arbitrary viewpoints to generate highly-realistic images. While the seminal paper of [Mildenhall et al. 2020] encoded this function as a Multi-Layer Perceptron (MLP), more recent works have proposed alternative representations based on spatial data structures such as voxel grids [Sara Fridovich-Keil and Alex Yu et al. 2022; Sun et al. 2022], plane-based factorizations [Chen et al. 2022], or multi-scale 3D hash grids [Müller et al. 2022]. Mip-NeRF [Barron et al. 2021] addressed aliasing issues by introducing an alternative rendering formulation based on conical frustums instead of rays, which was further expanded in [Barron et al. 2022] to account for unbounded scenes, and adapted to hash grid-based representations in [Barron et al. 2023]. In our work, we follow the Nerfacto model of [Tancik et al. 2023], which combines the field architecture from Instant-NGP [Müller et al. 2022] with the multi-stage proposals of MipNeRF-360 [Barron et al. 2022] to achieve a good trade-off between speed and quality.

2.1 NeRFs with Priors

Although the approaches discussed in the previous section achieve impressive visual fidelity, they generally struggle to represent under-constrained scene regions. Most NeRFs incorporate one or more heuristics to combat common artifacts such as “floaters,” e.g., by adding losses that promote peaked density [Barron et al. 2021, 2022; Hedman et al. 2021], injecting noise into the model during training [Mildenhall et al. 2020], or promoting surface smoothness [Oechsle et al. 2021; Wang et al. 2021; Zhang et al. 2021]. When data is insufficient or ambiguous, however, more effective priors are necessary to regularize the model.

In the few-shot setting, geometric priors have been shown to be particularly effective: pre-trained models can be used to supervise the NeRF with predicted depth [Deng et al. 2022; Roessle et al. 2022] or surface normals [Yu et al. 2022]. RegNeRF [Niemeyer et al. 2022] utilizes a combination of geometric (surface smoothness, sampling space annealing) and appearance (normalizing flow) regularizers to enable training a NeRF on as few as 3 images. Similarly, SinNeRF [Xu et al. 2022] proposes a semi-supervised learning approach using geometric and semantic pseudo labels to guide a NeRF reconstruction from a single view. In our work, we focus on scenes with denser coverage, where geometric priors have been observed to provide only marginal improvements [Niemeyer et al. 2022].

Other works focus on appearance-based priors, e.g., DiffusioNeRF [Wynn and Turmukhambetov 2023] uses a 2D denoising diffusion model trained on RGBD images to construct an unsupervised loss term, which encourages the NeRF to render plausible images from unobserved viewpoints. Finally, some approaches learn scene-based priors, by casting NeRF reconstruction as a generalization problem: MVSNet [Chen et al. 2021] constructs a cost volume that is encoded to a neural volume, allowing consistent renderings from only a few images. PixelNeRF [Yu et al. 2021] and GenVS [Chan et al. 2023] train an image encoder to lift few input views to 3D-aware neural representations that can be rendered from novel views. However, these methods are still limited by the availability of training data: approaches based on scene-based priors in particular tend to produce results that lack detail, or impose strong assumptions on scene content and rendering trajectory according to the types of scenes they were trained on. In contrast, our per-scene adversarial optimization approach avoids the need for any external data.

2.2 GANs for Image Refinement

Generative Adversarial Networks (GANs) [Goodfellow et al. 2014; Karras et al. 2020; Mescheder et al. 2018] are trained to produce images from a given data distribution by optimizing an adversarial loss. Initially proposed for unconditional image generation, GANs have also been applied to image-to-image translation and refinement tasks [Isola et al. 2017; Park et al. 2019; Wang et al. 2018a], such as colorization [Anwar et al. 2020], super-resolution [Ledig et al. 2017], and in-painting [Elharrouss et al. 2020]. In a similar setting, we optimize a conditional adversarial formulation based on StyleGAN2 [Karras et al. 2020] to refine the images produced by a NeRF to more closely match the data distribution of a given scene. A related idea is also explored concurrently to our work in NeRFLiX [Zhou et al. 2023], which trains a network in a non-adversarial

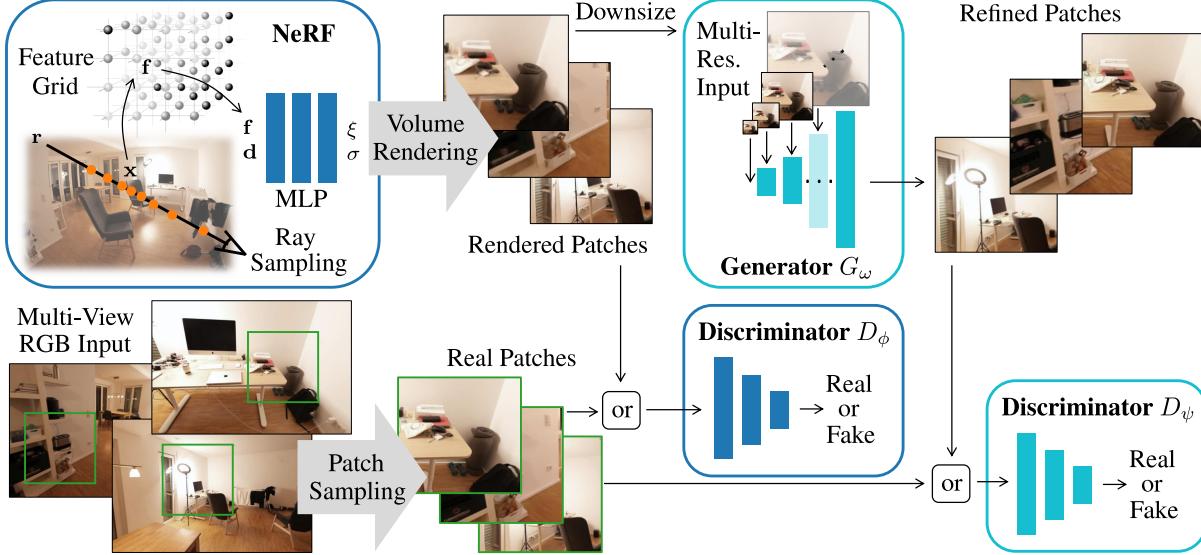


Fig. 2. GANeRF method overview: our method takes as input a set of posed images and optimizes for a 3D radiance field representation. Our core idea is to incorporate multi-view patch-based re-rendering constraints in an adversarial formulation that guides the NeRF reconstruction process, and to refine rendered images using a conditional generator network. Particularly in under-constrained regions this significantly improves the resulting rendering quality.

setting to invert NeRF artifacts. In contrast, the approach in [Zhou et al. 2023] requires training on multiple scenes and relies on a hand-crafted model to simulate NeRF noise.

3 METHOD

Given a set of posed input images capturing a static 3D scene, we focus on the problem of synthesizing novel views of that scene. We build on top of recent Neural Radiance Fields (NeRF) [Mildenhall et al. 2020], specifically, the Nerfacto model of [Tancik et al. 2023]. To improve realism in novel views, our method (Fig. 2) leverages a 2D adversarial loss that directly updates the 3D scene representation. To this end, a discriminator learns the distribution of image patches in the training data. Through adversarial training, the 3D NeRF representation (Sec. 3.1) is updated towards rendering patches that match this distribution (Sec. 3.2). On top of that, a 2D generator considers NeRF renderings at multiple resolutions, refining them based on feedback from a second discriminator (Sec. 3.3).

3.1 NeRF Preliminaries

NeRF models represent a scene by providing a density $\sigma_\theta(\mathbf{x})$ and an RGB color $\xi_\theta(\mathbf{x}, \mathbf{d})$ for each point $\mathbf{x} \in \mathbb{R}^3$ in 3D space, the color depending additionally on the viewing direction $\mathbf{d} \in \mathbb{R}^3$ to account for view-dependent effects. This radiance field representation ($\sigma_\theta, \xi_\theta$), which depends on learnable parameters θ , allows rendering a pixel of an image by casting a ray from the camera origin $\mathbf{o} \in \mathbb{R}^3$ through the pixel in the direction \mathbf{d} and by computing the expected observed color along the ray with a distribution depending on the density field [Mildenhall et al. 2020].

Formally, the rendering function for a radiance field $(\sigma_\theta, \xi_\theta)$ and ray \mathbf{r} is given by

$$\mathcal{R}_\theta(\mathbf{r}) := \int_0^\infty \sigma_\theta(\mathbf{r}_t) \exp \left[- \int_0^t \sigma_\theta(\mathbf{r}_s) ds \right] \xi_\theta(\mathbf{r}_t, \mathbf{d}) dt. \quad (1)$$

Here, $\mathbf{r}_t := \mathbf{o} + t\mathbf{d}$ is the 3D point along the ray at time t . $\mathcal{R}_\theta(\mathbf{r})$ can be approximated with the quadrature rule given samples of density and color along the ray [Mildenhall et al. 2020].

The NeRF parameters θ are typically optimized to minimize the expected, per-ray mean squared error, which penalizes differences between the rendered color and the ground-truth color. Specifically, given ray/color pairs (\mathbf{r}, \mathbf{c}) distributed as $p(\mathbf{r}, \mathbf{c})$, we minimize

$$\mathcal{L}_{\text{rgb}}^N(\theta) := \mathbb{E}_p \|\mathcal{R}_\theta(\mathbf{r}) - \mathbf{c}\|_2^2. \quad (2)$$

The superscript N distinguishes losses that are used to train NeRF from the ones used to train the generator, which are defined later.

3.2 NeRF Optimization with Discriminator

It is often the case that scenes are rich in repeated elements and surfaces often look similar even from different perspectives. Accordingly, patches from one view form a good prior for patches in other views. To encode this prior in our training scheme, we complement $\mathcal{L}_{\text{rgb}}^N$ with an adversarial objective $\mathcal{L}_{\text{adv}}^N(\theta, \phi)$ that leverages an auxiliary neural network D_ϕ (a.k.a. discriminator) parametrized by ϕ . The objective is optimized such that the discriminator is pushed towards classifying whether a given image patch is real or produced by the NeRF parametrized by θ (a.k.a. fake), while the NeRF is encouraged to fool the discriminator, thus rendering realistic patches. Patches P are assumed to be distributed according to $q(P)$ and we denote by \mathbf{r}_P the set of rays and by \mathbf{c}_P the pixel colors corresponding to patch P . The adversarial objective should be minimized with respect to the NeRF parameters θ as a proper loss, but maximized with respect to the discriminator parameters ϕ . Following [Mescheder et al. 2018], we adopt an R_1 gradient penalty term on the discriminator balanced by a nonnegative scalar λ_{gp}^N yielding the following

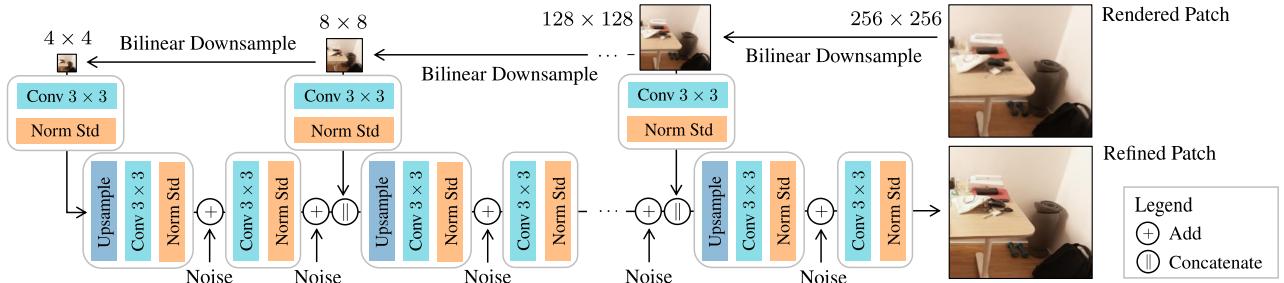


Fig. 3. Our conditional generator architecture consists of a feature extraction pyramid of six blocks operating at multiple resolutions: Starting from a 4×4 down-sampled patch, convolutional blocks extract level-specific features that are upsampled and added together with generative noise to the next feature extraction level. The final output resolution matches the input resolution of 256×256 .

form of the adversarial objective:

$$\mathcal{L}_{\text{adv}}^N(\theta, \phi) := \mathbb{E}_q [f(D_\phi(\mathcal{R}_\theta(\mathbf{r}_P))) + f(-D_\phi(\mathbf{c}_P)) - \lambda_{\text{gp}}^N \|\nabla D_\phi(\mathbf{c}_P)\|_2^2]. \quad (3)$$

Here, by setting $f(x) := -\log(1 + \exp(-x))$, we obtain a regularized version of the loss originally proposed in the seminal GAN paper [Goodfellow et al. 2014].

We further employ a perceptual loss based on VGG [Johnson et al. 2016], which has shown success in conjunction with 2D conditional GANs [Wang et al. 2018b]:

$$\mathcal{L}_{\text{perc}}^N(\theta) := \mathbb{E}_q [\|\Phi_{\text{VGG}}(\mathcal{R}_\theta(\mathbf{r}_P)) - \Phi_{\text{VGG}}(\mathbf{c}_P)\|_2^2], \quad (4)$$

where Φ_{VGG} is the vectorized concatenation of the first 5 feature layers before the max pooling operation of a VGG19 network [Simonyan and Zisserman 2015], each layer being normalized by the square root of the number of entries. $\mathcal{L}_{\text{perc}}^N(\theta)$ encourages similarity of real and fake patch features at different granularities.

The final loss that we minimize to train the NeRF is given by

$$\mathcal{L}_N(\theta) := \mathcal{L}_{\text{rgb}}^N(\theta) + \lambda_{\text{perc}}^N \mathcal{L}_{\text{perc}}^N(\theta) + \lambda_{\text{adv}}^N \max_{\phi \in \Psi} \mathcal{L}_{\text{adv}}^N(\theta, \phi), \quad (5)$$

where Φ denotes the set of possible discriminators and λ_*^N are non-negative balancing factors for the different losses. This objective is optimized with stochastic gradients computed from batches that combine rays and patches sampled uniformly across all training images (*i.e.* from the p and q distributions, respectively). Moreover, parameter updates are alternated between the NeRF and the discriminator to cope with the saddle-point problem, as usually done in GAN training schemes.

3.3 Conditional Generator

Up to this point, artifacts have been repaired directly in 3D through the discriminator guidance introduced in Sec. 3.2. However, the rendering quality can be further improved in 2D by postprocessing synthesized images. To this end, we design a conditional generator G_ω parameterized by ω , which takes as input a NeRF rendering and an auxiliary random vector \mathbf{z} and produces a cleaned image, thus serving as a stochastic denoiser. The architecture is inspired by the StyleGAN2 generator [Karras et al. 2020], but we adapt it to a conditional generator and omit the mapping network (Fig. 3). We keep the additive noise depending on \mathbf{z} , which is close in spirit to the way pix2pix [Isola et al. 2017] uses dropout as source of

randomness in their conditional GAN setting. As shown in Fig. 3, the conditioning input patch is 6 times bilinearly downsampled by a factor of 2, thus enabling a multi-scale analysis. The downsampled patches are encoded with a convolutional layer into 32 feature channels, which are concatenated to the output of the generator layer of corresponding scale. As in StyleGAN2, we use leaky ReLU activations, input/output skip connections and normalization layers. Additive noise is injected after the normalization layers, and noise is additionally scaled by a learnable per-layer factor.

Akin to the NeRF optimization, the generator is trained in a regularized adversarial setting. This involves a second discriminator D_ψ parameterized by ψ , which differs from the previously introduced D_ϕ . Indeed, the NeRF and the conditional generator introduce different types of errors in the output image that can be addressed more effectively by independent discriminators. The adversarial objective $\mathcal{L}_{\text{adv}}^G$ used to train the generator takes the following form:

$$\mathcal{L}_{\text{adv}}^G(\omega, \psi | \theta) := \mathbb{E}_{q,n} [f(D_\psi(G_\omega(\mathcal{R}_{\perp\theta}(\mathbf{r}_P), \mathbf{z}))) + f(-D_\psi(\mathbf{c}_P)) - \lambda_{\text{gp}}^G \|\nabla D_\psi(\mathbf{c}_P)\|_2^2], \quad (6)$$

where the expectation is additionally taken with respect to \mathbf{z} distributed as a standard normal distribution $n(\mathbf{z})$. The adversarial objective should be minimized with respect to the generator’s parameters ω , but maximized with respect to the discriminator parameter ψ . Moreover, we stop the gradient through the NeRF parameters θ , which is denoted by $\perp\theta$.

The adversarial objective is complemented with the same perceptual loss used to train the NeRF, namely

$$\mathcal{L}_{\text{perc}}^G(\omega | \theta) := \mathbb{E}_{q,n} [\|\Phi_{\text{VGG}}(G_\omega(\mathcal{R}_{\perp\theta}(\mathbf{r}_P), \mathbf{z})) - \Phi_{\text{VGG}}(\mathbf{c}_P)\|_2^2] \quad (7)$$

and an L_1 color loss, as in the conditional GAN pix2pix [Isola et al. 2017], operating on patches, defined as:

$$\mathcal{L}_{\text{rgb}}^G(\omega | \theta) := \mathbb{E}_{q,n} [\|G_\omega(\mathcal{R}_{\perp\theta}(\mathbf{r}_P), \mathbf{z}) - \mathbf{c}_P\|_1]. \quad (8)$$

The overall generator loss is defined as

$$\mathcal{L}_G(\omega | \theta^\star) := \lambda_{\text{perc}}^G \mathcal{L}_{\text{perc}}^G(\omega | \theta^\star) + \lambda_{\text{rgb}}^G \mathcal{L}_{\text{rgb}}^G(\omega | \theta^\star) + \max_{\psi \in \Psi} \mathcal{L}_{\text{adv}}^G(\omega, \psi | \theta^\star), \quad (9)$$

where Ψ denotes the set of possible discriminators, $\lambda_{*\theta}^G$ are nonnegative factors balancing the loss components, and θ^\star is the parametrization of the NeRF obtained by optimizing \mathcal{L}_N . We cope with the

saddle-point problem by alternating updates of the generator and the discriminator akin to what we have described for \mathcal{L}_N .

4 EXPERIMENTS

4.1 Datasets and Metrics

4.1.1 ScanNet++. From the ScanNet++ [Yeshwanth et al. 2023] dataset, we evaluate on five indoor scenes consisting of office, lab and apartment environments. Each scene contains an average of ~ 700 images, ~ 20 of which are defined as a test set. In contrast to other datasets commonly considered in NeRF works (e.g. LLFF [Mildenhall et al. 2020] or the 360° scenes from [Barron et al. 2022]), the test views in ScanNet++ are selected to be spatially out-of-distribution compared to the training views, in order to explicitly evaluate a model’s generalization capabilities (see supplement for capture details).

4.1.2 Tanks and Temples. As a benchmark for larger-scale reconstruction, we consider four scenes from the advanced set of scenes of the Tanks and Temples [Knapitsch et al. 2017] dataset: Auditorium, Ballroom, Courtroom, and Museum. These scenes depict large indoor environments, with detailed geometries and complex illumination conditions. For each scene, we randomly select 10% of the available images as a test set, resulting in a split of ~ 270 training and ~ 30 test views on average.

4.1.3 Evaluation Metrics. We evaluate our results in terms of three main visual quality metrics: PSNR, SSIM [Wang et al. 2004], and LPIPS [Zhang et al. 2018]. Following previous works in the image generation literature, we additionally report KID [Bińkowski et al. 2018] scores, which measure how closely our model’s outputs match the visual distribution of the scene.

4.2 Training and Implementation Details

4.2.1 NeRF. In each training iteration, we render 4096 random rays and a 256×256 patch from a single random input image. The perceptual loss processes the patch as a whole, whereas the adversarial loss subdivides it into 16 smaller patches of size 64×64 without overlap. D_ϕ is a StyleGAN2 discriminator [Karras et al. 2020], which is adapted to process 64×64 patches with the number of convolutional channels reduced by half. For each generated “fake” patch the discriminator is also given a real patch. The radiance field and discriminator D_ϕ are trained using the Adam [Kingma and Ba 2015] and RMSprop [Tieleman and Hinton. 2012] optimizers, respectively.

4.2.2 Conditional Generator. The initial training patch size before downsampling is 256×256 . At inference time, however, the generator is able to run fully convolutionally on high-resolution images to refine the NeRF renderings. The generator is trained using a batch size of 8. While the perceptual loss operates on the full training patches, the adversarial loss subdivides each patch into 4 smaller patches of size 128×128 without overlap, thus D_ψ is trained with batch size 32. The discriminator is inspired by StyleGAN2 [Karras et al. 2020], and adapted to process 128×128 patches. Both generator and discriminator D_ψ are trained using the Adam optimizer [Kingma and Ba 2015]. Further training details are in the supplement.

Method	PSNR↑	SSIM↑	LPIPS↓	KID↓
Mip-NeRF 360 [Barron et al. 2022]	24.9	0.862	0.225	0.0241
Instant NGP [Müller et al. 2022]	25.3	0.844	0.269	0.0511
Nerfacto [Tancik et al. 2023]	25.6	0.848	0.245	0.0398
Nerfacto + extra capacity	25.9	0.854	0.228	0.0314
Nerfacto + pix2pix [Isola et al. 2017]	24.9	0.848	0.193	0.0162
Ours w/o discriminator	25.8	0.857	0.177	0.0143
Ours w/o generator	25.9	0.860	0.198	0.0169
Ours	26.1	0.864	0.161	0.0113

Table 1. Quantitative results on five ScanNet++ scenes. Our method outperforms the baselines by a large margin in the perceptual metrics, like LPIPS and KID, while maintaining consistently better PSNR and SSIM scores.

Method	PSNR↑	SSIM↑	LPIPS↓	KID↓
Mip-NeRF 360 [Barron et al. 2022]	18.5	0.709	0.327	0.0277
Instant NGP [Müller et al. 2022]	19.3	0.700	0.369	0.0466
Nerfacto [Tancik et al. 2023]	19.5	0.716	0.329	0.0432
Nerfacto + extra capacity	19.6	0.733	0.291	0.0314
Nerfacto + pix2pix [Isola et al. 2017]	20.6	0.739	0.242	0.0115
Ours w/o discriminator	20.6	0.745	0.192	0.0102
Ours w/o generator	19.9	0.739	0.251	0.0130
Ours	20.9	0.776	0.169	0.0065

Table 2. Quantitative results on four Tanks and Temples scenes. Our method achieves particularly strong improvements on the perceptual metrics, thus improving visual details and sharpness of novel view renderings.

4.3 Baseline Comparisons

We compare our approach to several baselines and methods from recent literature. We pick Mip-NeRF 360 [Barron et al. 2022] and Instant NGP [Müller et al. 2022] as representatives of the current state of the art in NeRF architectures optimized for visual quality and speed, respectively. Furthermore, we evaluate three variations of the Nerfacto [Tancik et al. 2023] model that our proposed approach is based upon: i) the baseline model with no modifications (Nerfacto); ii) a higher-capacity variation, which has $\sim 25\%$ more parameters than our NeRF + generator pair (Nerfacto + extra capacity); and iii) Nerfacto followed by a pix2pix [Isola et al. 2017] generator while keeping the NeRF fixed (Nerfacto + pix2pix). Details on these Nerfacto variants are in the supplement. The baselines and our method use the same parameters across all scenes and datasets.

As shown in Tab. 1 and Tab. 2, our approach leads to noticeable improvements in all metrics when compared to baselines. In particular, the two perceptual metrics (LPIPS, KID) demonstrate the largest relative improvements, suggesting that our approach is able to fix many of the small visual artifacts that are often poorly measured by color similarity metrics (PSNR, SSIM). This is also confirmed by the qualitative evaluation shown in Figs. 4 and 5. Our method outperforms the baseline Nerfacto + pix2pix, even though both approaches utilize a perceptual loss. Furthermore, our ablated version without a discriminator during NeRF optimization achieves better performance, demonstrating the effectiveness of our generator.

4.4 Ablation Experiments

To verify the effectiveness of the added components, we perform an ablation study on the ScanNet++ and Tanks and Temples datasets.

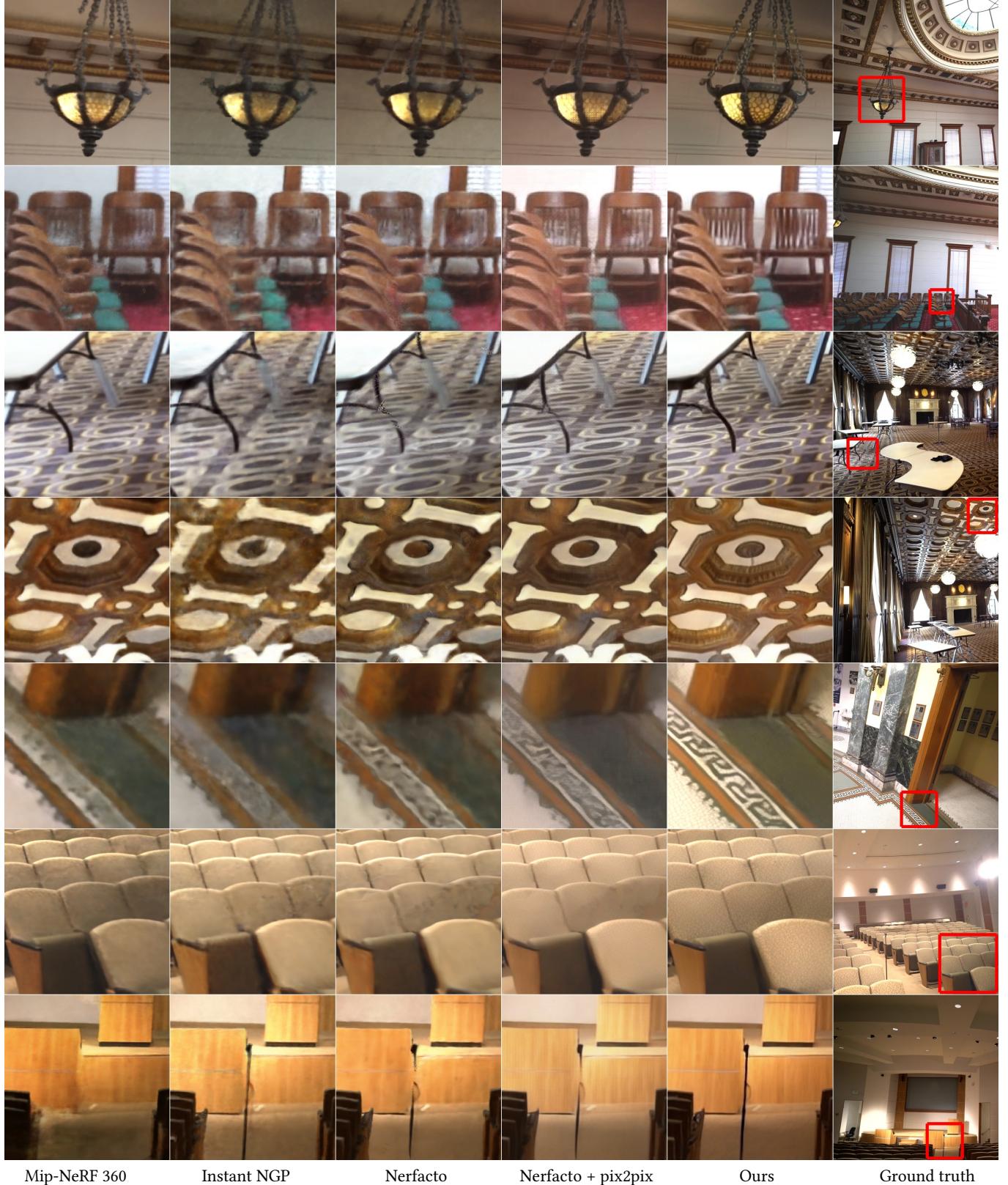


Fig. 4. Comparison on Tanks and Temples. Our method recovers more detail than the baselines, such as thin structures or patterns in on the floor.

The quantitative results (Tab. 1 and Tab. 2), as well as the qualitative results in Fig. 6 show that the complete version of our method achieves the highest performance. Further ablation results on ScanNet++ are provided in the supplement.

Without Discriminator. In this experiment, we investigate the impact of optimizing the radiance field solely with an RGB loss and applying our generator as a pure post-processing step on the renderings. We observe that the geometry and texture details of the scene cannot be recovered to the same extent as achieved with our full method (Fig. 6). The drop in all metrics (“w/o discriminator” in Tabs. 1 and 2) clearly highlights the importance of the patch-based supervision to inform the NeRF representation in 3D. This indicates that our method, which incorporates gradient backpropagation to the 3D representation, surpasses a pure 2D post-processing approach.

Without Generator. When omitting the generator, the results are less sharp (e.g., samples 4, 5, and 7 in Fig. 6), which leads to lower performance compared to the full version of our method (“w/o generator” in Tabs. 1 and 2). This shows that the generator helps to achieve high-detail renderings.

NeRF Training. Tab. 3 provides more detailed ablations on the NeRF optimization, which show that dropping the adversarial loss (“w/o adv. loss”) or dropping the perceptual loss (“w/o perc. loss”) have a negative impact on performance.

Generator Training. Detailed ablations on the generator training are listed in Tab. 3. We investigate the impact of omitting specific input patch resolutions in our model. Removing the two highest resolutions out of the six resolutions results in a noticeable performance drop (“w/o high-res. patches”), highlighting the essential role of high-resolution input for the generator. Conversely, when the two lowest resolutions are removed (“w/o low-res. patches”), we observe a decline in quality that indicates that the generator also relies on the low-resolution input. We further show that the small RGB encoder, i.e., one convolutional layer on the multi-resolution patches (Fig. 3), benefits the generator (“w/o RGB encoding”).

Furthermore, our ablation experiments examine the individual loss functions, namely the adversarial loss (“w/o adv. loss”), perceptual loss (“w/o perc. loss”), and L1 RGB loss (“w/o RGB loss”). The results reveal that each of these loss functions contributes significantly to the overall performance of the generator.

Reduced Number of Images. Tab. 4 lists results when reducing the number of images of the largest scene (800 images) to 400, 200, and 100 images. It shows that our method consistently outperforms Nerfacto by a similar margin as observed in the more dense setting.

4.5 Limitations

Our results show that we can achieve significant improvements compared to state-of-the-art methods. At the same time, we believe there are still important limitations. For instance, at the moment our patch discriminator is trained per scene. However, it would be beneficial to train a more generic prior that has access to a larger scene corpus to improve its capability. While feasible, a naive generalizable discriminator would tend to collapse to a scene classifier;

Method	PSNR↑	SSIM↑	LPIPS↓	KID↓
Nerfacto [Tancik et al. 2023]	21.1	0.843	0.304	0.0378
Ours	22.3	0.862	0.158	0.0107
w/o discriminator	21.9	0.857	0.178	0.0178
w/o generator	21.7	0.854	0.247	0.0155
NeRF training				
w/o adv. loss	21.9	0.861	0.175	0.0110
w/o perc. loss	21.7	0.857	0.187	0.0194
Generator training				
w/o high-res. patches	22.1	0.851	0.179	0.0176
w/o low-res. patches	22.1	0.862	0.159	0.0109
w/o RGB encoding	22.1	0.860	0.167	0.0122
w/o adv. loss	22.3	0.861	0.174	0.0122
w/o perc. loss	21.7	0.834	0.184	0.0110
w/o RGB loss	21.8	0.859	0.163	0.0109

Table 3. Ablation study on Auditorium scene from Tanks and Temples. The decline in performance when removing individual parts of our method confirms our design choices.

Method	# images	PSNR↑	SSIM↑	LPIPS↓	KID↓
Nerfacto [Tancik et al. 2023]	800	24.2	0.844	0.247	0.0661
Ours		24.7	0.870	0.169	0.0157
Nerfacto [Tancik et al. 2023]	400	24.2	0.843	0.252	0.0752
Ours		24.3	0.864	0.169	0.0161
Nerfacto [Tancik et al. 2023]	200	23.5	0.825	0.274	0.0837
Ours		23.9	0.862	0.182	0.0203
Nerfacto [Tancik et al. 2023]	100	22.2	0.805	0.307	0.1076
Ours		22.5	0.842	0.216	0.0253

Table 4. Ablation study with reduced number of images on a large ScanNet++ scene. Our method consistently outperforms Nerfacto by a similar margin, regardless of the level of input sparsity.

i.e., it would primarily identify whether a patch belongs to the same scene or not. To overcome this issue, one possible solution is to train a NeRF representation for each training scene simultaneously, which would entail considerable computational expenses. Another limitation is that we currently focus only on static scenes; however, we believe it would be interesting to expand our approach to recent deformable and dynamic NeRF approaches such as [Işık et al. 2023; Kirschstein et al. 2023; Park et al. 2021; Tretschk et al. 2021].

5 CONCLUSION

We introduce GANeRF, a new approach for adversarial optimization of neural radiance fields. The main idea behind our approach is to impose patch-based rendering constraints into the radiance field reconstruction. By backpropagating gradients from a scene patch discriminator, we effectively address typical imperfections and rendering artifacts stemming from traditional NeRF methods. In particular, in regions with limited coverage, this significantly improves rendering quality, both qualitatively and quantitatively outperforming state-of-the-art methods. At the same time, our method is only a stepping stone for combining rendering priors with high-end novel view synthesis. For instance, we believe that generalizing across scenes will offer numerous opportunities for leveraging similar ideas as those proposed in this work.

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Fig. 5. Comparison on Scannet++. Our method produces less foggy artifacts, which leads to sharper renderings compared to the baselines.

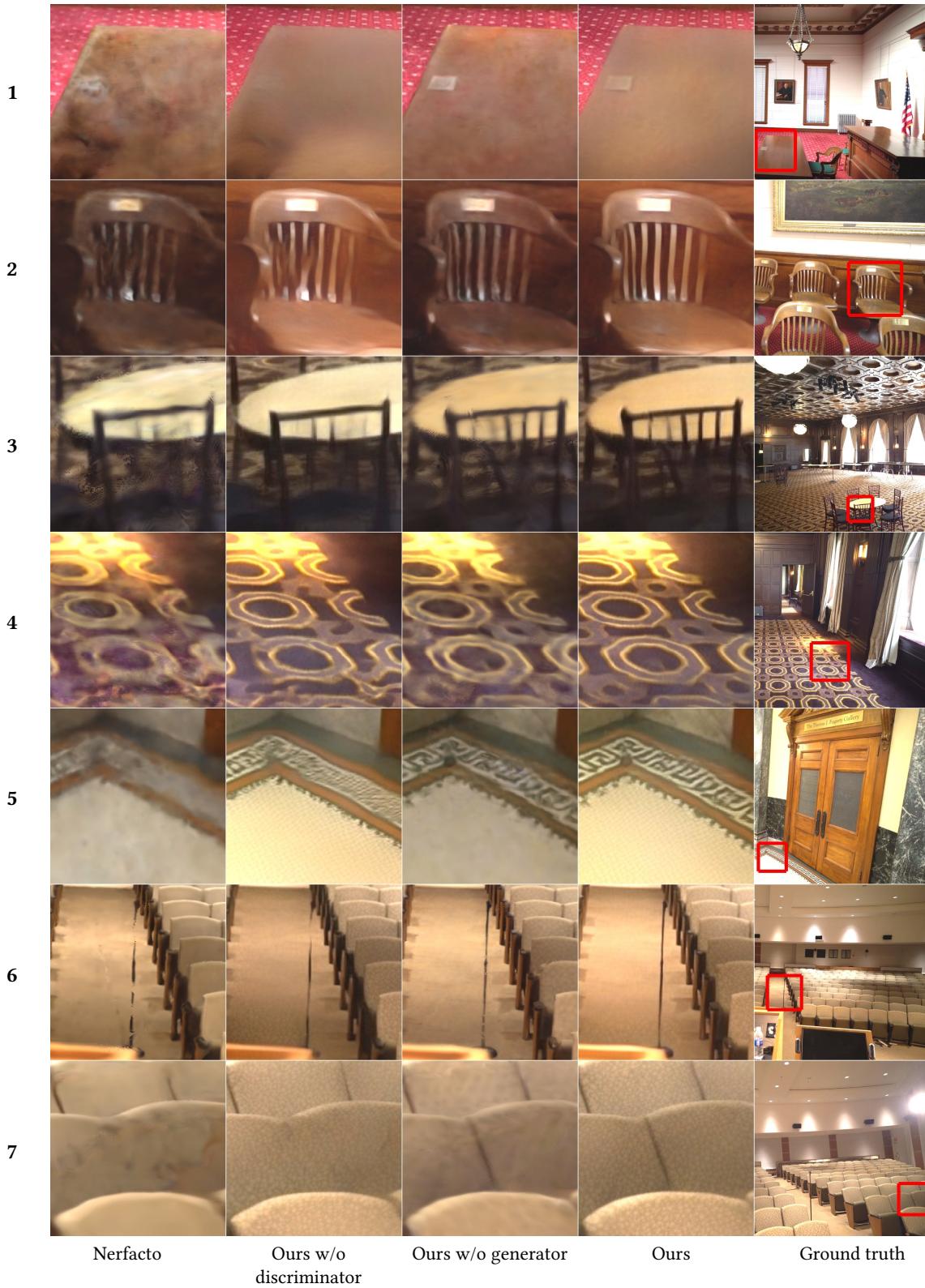


Fig. 6. Ablation experiments on Tanks and Temples. “Ours w/o discriminator” significantly struggles with patterns (samples 4 and 5) and misses thin structures (samples 3 and 6). “Ours w/o generator” better recovers the patterns but produces blurry results compared to the full method (samples 4, 5 and 7).

A QUALITATIVE RESULTS

Figs. 7 and 8 show more qualitative results on ScanNet++ [Yeshwanth et al. 2023] and Tanks and Temples [Knapitsch et al. 2017]. Through our NeRF training with discriminator and the multi-resolution conditional generator, our renderings contain more detail and fewer artifacts compared to the baseline methods, Mip-NeRF 360 [Barron et al. 2022], Instant NGP [Müller et al. 2022], Nerfacto [Tancik et al. 2023] and Nerfacto + pix2pix [Isola et al. 2017].

B ABLATION EXPERIMENTS ON SCANNET++

Tab. 5 lists the same ablation experiments for ScanNet++ as shown for Tanks and Temples in the main paper. The full version of our method achieves the best performance. Similar to the Tanks and Temples ablation experiments, the results confirm the design choices with regards to loss functions of NeRF and the generator, as well as the generator architecture using both low- and high-resolution patches with a convolutional RGB encoding.

C TRAINING AND IMPLEMENTATION DETAILS

NeRF. The radiance field and discriminator D_ϕ are trained for 400k iterations, using the Adam optimizer [Kingma and Ba 2015] with learning rate 1×10^{-2} for NeRF, and RMSprop [Tieleman and Hinton. 2012] with learning rate 1×10^{-3} for the discriminator. The loss weights are set to $\lambda_{\text{adv}}^N = 0.0003$, $\lambda_{\text{perc}}^N = 0.0003$ and $\lambda_{\text{gp}}^N = 0.1$.

Conditional Generator. Both generator and discriminator D_ψ are trained for 3000 epochs using the Adam optimizer [Kingma and Ba 2015] with learning rate 2×10^{-3} . The loss weights are set to $\lambda_{\text{perc}}^G = 1.0$, $\lambda_{\text{rgb}}^G = 3.0$ and $\lambda_{\text{gp}}^G = 5.0$.

D DATASET DETAILS

ScanNet++. From the ScanNet++ [Yeshwanth et al. 2023] dataset, we use DSLR camera images, captured at high resolution (4672×7008). They are provided with camera poses which were computed using the structure from motion pipeline COLMAP [Schönberger and Frahm 2016]. We undistort the images and resize them to 768×1152 .

Tanks and Temples. On the Tanks and Temples dataset [Knapitsch et al. 2017] we use the original resolution of 1080×1920 .

E BASELINE COMPARISON DETAILS

For a fair comparison, we train all baselines until convergence. For the Nerfacto-based methods we let them run for 400k iterations.

Nerfacto + extra capacity. The Nerfacto baseline with extra capacity doubles the number of hidden dimensions of the MLPs, doubles the grid resolution, and increases the hash table size by 4 compared to the default Nerfacto. This results in a total of $\sim 44M$ trainable parameters, which is $\sim 25\%$ more than our model (NeRF + Generator) and ~ 3.4 times the number of parameters of the default Nerfacto model ($\sim 12.9M$).

Nerfacto + pix2pix. From the official pix2pix [Isola et al. 2017] repository, we found that the generator variant using 9 ResNet [He et al. 2016] blocks combined with Wasserstein training objective

Method	PSNR↑	SSIM↑	LPIPS↓	KID↓
Nerfacto [Tancik et al. 2023]	24.2	0.844	0.247	0.0661
Ours	24.7	0.870	0.169	0.0157
w/o discriminator	24.4	0.859	0.188	0.0194
w/o generator	24.6	0.865	0.201	0.0294
NeRF training				
w/o adv. loss	24.4	0.867	0.170	0.0172
w/o perc. loss	24.5	0.866	0.184	0.0229
Generator training				
w/o high-res. patches	24.2	0.849	0.202	0.0188
w/o low-res. patches	24.6	0.870	0.171	0.0180
w/o RGB encoding	24.6	0.870	0.171	0.0179
w/o adv. loss	24.7	0.869	0.175	0.0184
w/o perc. loss	24.4	0.858	0.170	0.0217
w/o RGB loss	24.6	0.869	0.170	0.0172

Table 5. Ablation study on a ScanNet++ scene. Removing individual parts of our methods leads to a decline in performance, indicating the importance of the different architectural choices and training strategies.

with gradient penalty [Gulrajani et al. 2017] achieves best performance. We equally train this model with the VGG perceptual loss, which improves its performance. Hence, the comparison between “Ours w/o discriminator” and “Nerfacto + pix2pix” evaluates the performance of our generator against the pix2pix generator, both on top of Nerfacto. This comparison shows that our generator performs better than the pix2pix generator across both datasets.

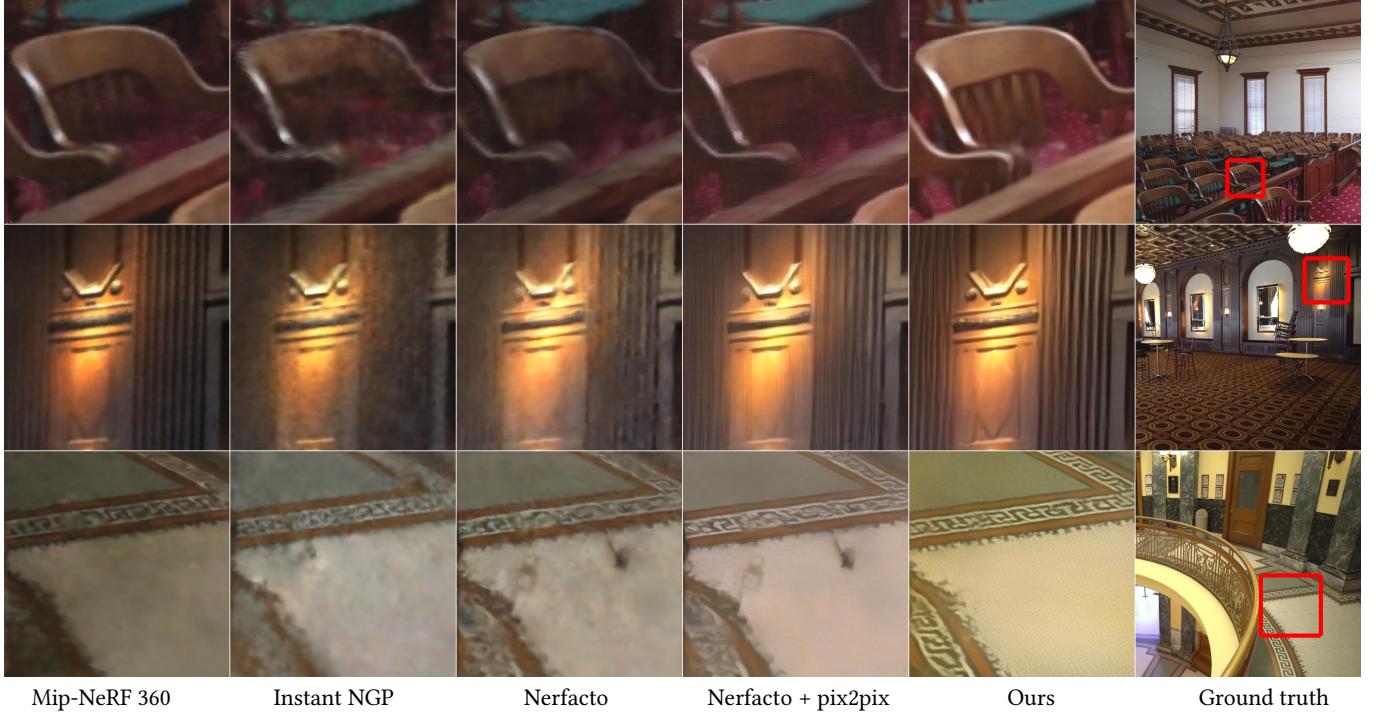


Fig. 7. Baseline comparison on Tanks and Temples. Our method is able to recover the chair struts, or floor texture in a more accurate way than the baselines, which produce noticeable artefacts.

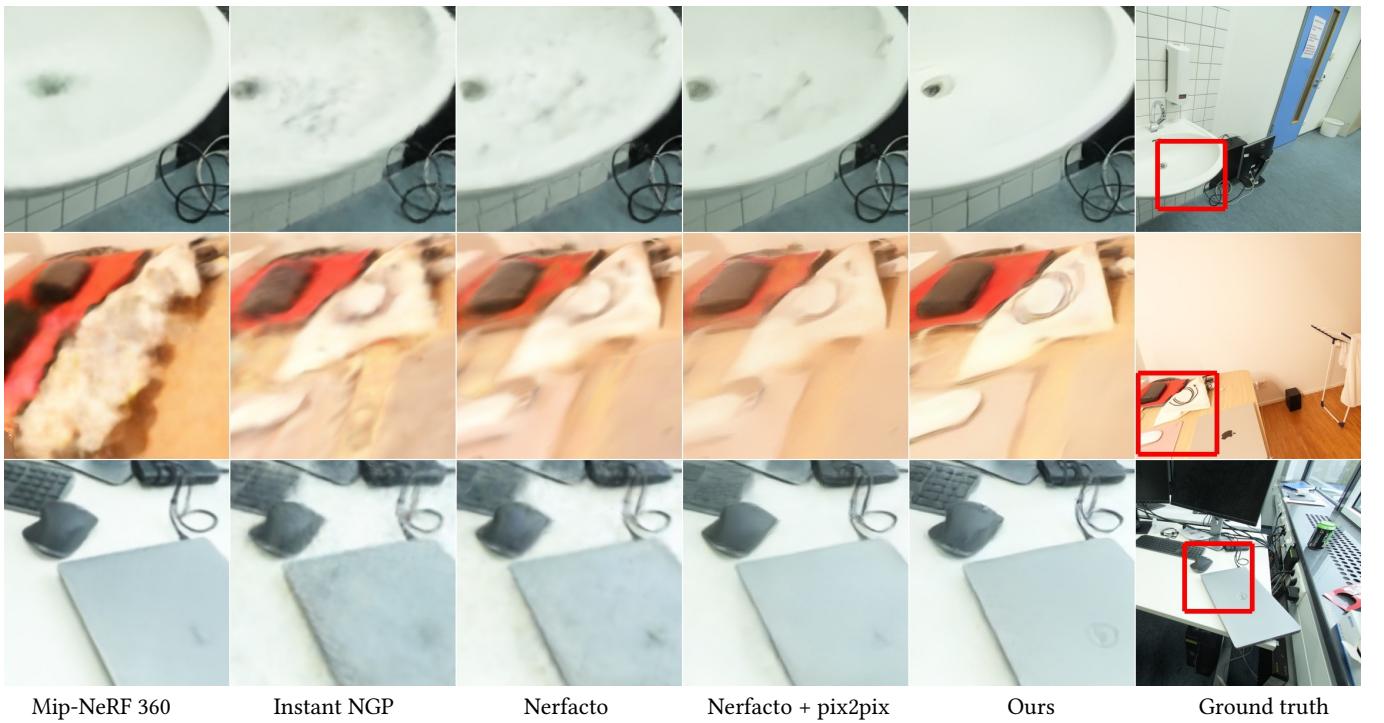


Fig. 8. Baseline comparison on ScanNet++. Compared to the baselines, our method does not show floating artifacts on the sink sample and achieves the sharpest renderings of the tabletop objects.