

NeRF-US : Removing Ultrasound Imaging Artifacts from Neural Radiance Fields in the Wild

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rishitdagli.com/nerf-us/

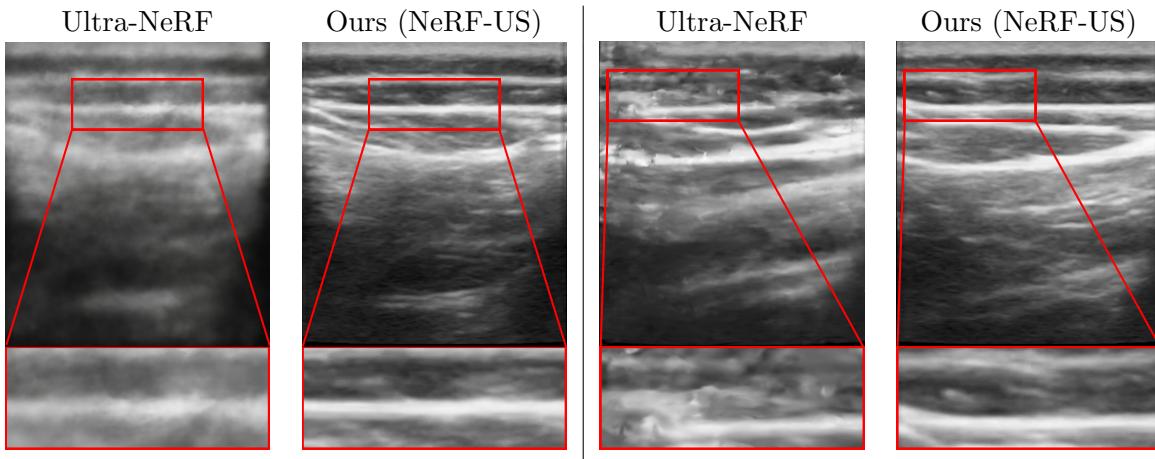


Figure 1: Comparison of novel ultrasound views rendered by Ultra-NeRF (Wysocki et al., 2024) (left) and our NeRF-US (right). These reconstructions are of the human knee featuring an anteroposterior view (left) and a lateral view (right). Our approach, NeRF-US, significantly improves the quality of the reconstructions, making these suitable for any subsequent downstream clinical tasks.

Abstract

Current methods for performing 3D reconstruction and novel view synthesis (NVS) in ultrasound imaging data often face severe artifacts when training NeRF-based approaches. The artifacts produced by current approaches differ from NeRF floaters in general scenes because of the unique nature of ultrasound capture. Furthermore, existing models fail to produce reasonable 3D reconstructions when ultrasound data is captured or obtained casually in uncontrolled environments, which is common in clinical settings. Consequently,

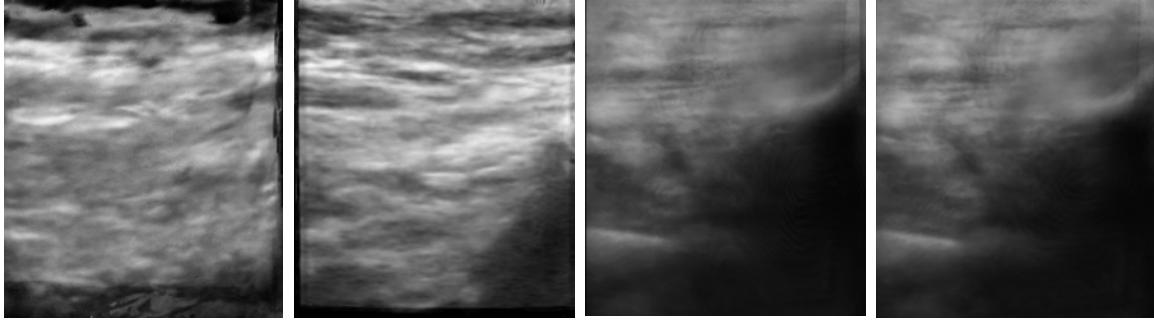


Figure 2: We observe the existence of multiple NeRF artifacts in ultrasound imaging which is a common challenge in medical NeRF-based methods.

existing reconstruction and NVS methods struggle to handle ultrasound motion, fail to capture intricate details, and cannot model transparent and reflective surfaces. In this work, we introduced NeRF-US, which incorporates 3D-geometry guidance for border probability and scattering density into NeRF training, while also utilizing ultrasound-specific rendering over traditional volume rendering. These 3D priors are learned through a diffusion model. Through experiments conducted on our new “Ultrasound in the Wild” dataset, we observed accurate, clinically plausible, artifact-free reconstructions.

1. Introduction

All imaging systems benefit from capturing the 3D geometry of the scenes being imaged. Capturing the 3D geometry of scenes is crucial in medical imaging, not only for accurate diagnosis but also for effective treatment planning. This is particularly vital in conditions like hemophilic arthropathy, where joint bleeds lead to synovial proliferation and effusion, and the measurement of synovial fluid volume is a common diagnostic step. Among the key indicators of disease activity in the joints is synovial recess distention (SRD), which may arise from various factors such as accumulation of blood or synovial fluid (Heilmann et al., 1996). Similarly, diagnosing conditions such as scoliosis requires understanding the volumetric properties of the spine (Kadoury et al., 2007, 2009). Producing robust and accurate 3D representations while performing view synthesis from 2D medical imaging techniques is an important problem that can be used for planning and downstream clinical tasks (Thomas W. Hash, 2013; Jackson et al., 1988; Ji et al., 2011).

We are interested in the problem of 3D reconstruction and novel view synthesis for ultrasound imaging. We focus our efforts on working with ultrasound imaging because it is one of the most cost-effective and accessible forms of medical imaging. We are interested in performing this task on casually captured or in the wild ultrasounds since all ultrasounds captured by clinicians are casually captured. Furthermore, performing this task with ultrasound imaging is also a very challenging task due to the nature of how ultrasounds are captured. This task has traditionally been performed by training clinicians to mentally assemble a 3D image. There have been some digital techniques towards the creation of such 3D ultrasound images which relied on utilizing advanced wobbler probes (Morgan et al.,

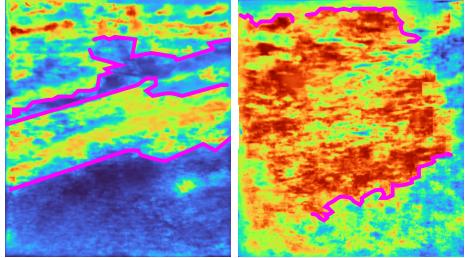


Figure 3: We show a depth map of two reconstructions produced by our approach, NeRF-US. We superimpose the depth map with tissue boundaries as shown by color-coded curves. Our approach produces accurate representations with the tissue boundaries unambiguously reconstructed.

2018), 2D transducers (Smith et al., 2002), or tracking probes (Poon and Rohling, 2005). These kinds of approaches are often based upon assembling a 3D image from multiple 2D slices and use a lot of handcrafted priors. Thus, these classes of approaches often have many limitations, primarily these approaches are often unable to produce plausible 3D reconstructions that could be used for downstream tasks (Kojcev et al., 2017). Such manual and digital approaches end up being very costly, error-prone, and irreproducible (Kojcev et al., 2017; Lyshchik et al., 2004).

Some recently learned digital approaches based on neural radiance field (Mildenhall et al., 2021) methods have also been developed that work toward the problem we highlight (Wysocki et al., 2024; Gaits et al., 2024; Li et al., 2021a). These kinds of approaches have also successfully been used in other medical contexts like reconstructing CT projections from X-ray (Corona-Figueroa et al., 2022a) and surgical scene 3D reconstruction (Wang et al., 2022; Zha et al., 2023) which have shown impressive results. However, using such methods for ultrasound imaging does not produce artifact-free 3D representations from casually captured ultrasounds.

There are a few challenges common across all these learned digital methods: the need for high-quality diverse datasets that capture intricate details like tissue interface locations in high detail, accurately modeling transparent and reflective surfaces, specular surface rendering, and delineating boundaries between different tissues. We qualitatively show some NeRF artifacts that appear when Ultra-NeRF is adopted (Wysocki et al., 2024) on ultrasound images in the wild in Figure 2. These challenges are common across all medical NeRF-based methods. In contrast, our approach, NeRF-US, produces artifact-free reconstructions with minor details that are accurately reconstructed, as shown in Figure 3.

Towards the problem of producing high-quality ultrasound reconstructions in the 'wild', we propose our approach, NeRF-US. Our goal is to produce a 3D representation given a set of ultrasound images taken in the wild and their estimated camera or ultrasound probe positions. We first train a 3D denoising diffusion model which serves as geometric priors for the reconstruction. We then train a NeRF model that takes in a 3D vector (denoting positions in 3D) and learns a 5D vector (attenuation, reflectance, border probability, scattering density, and scattering intensity) following the success of Ultra-NeRF (Wysocki et al., 2024). While training this NeRF, we incorporate the geometric priors from the diffusion model to guide the outputs for border probability and scattering density. This allows our approach, NeRF-US, to accurately generate 3D representations for ultrasound imaging in the 'wild', as shown in Figure 1. We also evaluate our approach with a new dataset for this task, which we will release publicly. To the best of our knowledge, ours is the first approach

that handles this challenging task of reconstructing noniconic, nonideal ultrasound images in the ‘wild’ and also outperforms previous methods.

Our approach is universal in ultrasound imaging and our experiments include human spine and knee joint ultrasound. We observe that current evaluation and management strategies for painful musculoskeletal episodes in patients with hemophilia often rely on subjective evaluations, leading to discrepancies between patient-reported symptoms and imaging findings. Ultrasonography (US) has emerged as a valuable tool for assessing joint health due to its accessibility, safety, and ability to detect soft tissue changes, including joint recess distension, with precision comparable to magnetic resonance imaging (MRI). However, accurately interpreting US images, especially in identifying and quantifying recess distention, remains challenging for clinicians. Providing clinicians with a 3D representation of recess distension acquired from US cine loops could greatly enhance their ability to appreciate the extent of fluid accumulation within the joint space. This information is crucial for guiding treatment decisions, especially regarding the initiation and optimization of hemostatic therapy and the utilization of adjunctive treatments such as physical therapy and anti-inflammatory agents. Thus, our new “Ultrasound in the wild” dataset is focused on ultrasounds around the knee for the recess distention problem.

Addressing the challenge of casually captured ultrasounds, which is the common practice among clinicians today, NeRF-US integrates specific ultrasound properties within the NeRF framework. This integration not only surpasses existing methods in producing artifact-free 3D reconstructions, but also expands the potential applications beyond routine medical diagnostic tasks. For example, the ability to generate accurate and artifact-free 3D models from ultrasound data can significantly enhance surgical planning and postoperative evaluations. In addition, our approach aims to increase the use of cost-effective methods such as ultrasound, offering a viable alternative to more expensive imaging techniques for certain medical scenarios.

Contributions. Modern 3D reconstruction methods for ultrasound imaging are either overly reliant on hand-crafted priors, manual intervention, or are unable to work on ultrasound imaging in the ‘wild’. The key novelty of our approach stems from the modification of NeRF-based methods for this task.

- We propose a first-of-its-kind approach for training NeRFs on ultrasound imaging that incorporates the properties of ultrasound imaging and incorporates 3D priors through a diffusion model to reconstruct accurate images in uncontrolled environments.
- We introduce a new dataset, “Ultrasound in the Wild”, featuring real, non-iconic ultrasound imaging of the human knee. This dataset will serve as a resource for benchmarking NVS performance on ultrasound imaging under real-world conditions and will be made publicly available.
- Our approach demonstrates improved qualitative and quantitative performance by significantly reducing or eliminating ultrasound imaging artifacts. This leads to more accurate 3D reconstructions compared to other medical and non-medical NeRF-based methods. Furthermore, we observe clinically plausible 3D reconstructions from ultrasound imaging in the ‘wild’.

We open-source our code and data on our project webpage.

2. Related Works

Implicit Neural Representations and View Synthesis. Historically, the field of novel view synthesis relied on traditional techniques like image interpolation (Chaurasia et al., 2013; Chen and Williams, 2023, 1993; Debevec et al., 2023, 1996; Fitzgibbon et al., 2005; Seitz and Dyer, 1996; McMillan and Bishop, 2023, 1995) and light field manipulation (Sloan et al., 1997; Levoy and Hanrahan, 1996) to generate new views without needing to understand the geometry of the scene. These methods worked best with densely sampled scenes, which limited their usability. The advent of learned techniques, popularized using image blending (Flynn et al., 2016; Hedman et al., 2018) and multiplane images (Li et al., 2020; Mildenhall et al., 2019). Further progress involved creating explicit 3D scene representations through meshes (Debevec et al., 1998; Riegler and Koltun, 2020; Shan et al., 2013), point clouds (Qi et al., 2017; Aliev et al., 2020; Bui et al., 2018; Grossman and Dally, 1998), and voxel grids (Kutulakos and Seitz, 1999; Penner and Zhang, 2017; Seitz and Dyer, 1999), offering a better understanding of scene geometry but with many challenges in model accuracy and robustness.

The introduction of neural implicit representations (INRs) marked a change in representing 3D scenes, offering a more adaptable and comprehensive method for encoding both the geometric and appearance aspects of scenes (Sitzmann et al., 2019, 2020). Utilizing neural networks as a foundation, this approach allowed for the implicit modeling of scene geometry, with the capacity to generate novel views through ray-tracing techniques. By interpreting a scene as a continuous neural-based function, INRs map 3D coordinates to color intensity. Among the diverse neural representations for 3D reconstruction and rendering, the success of deep learning has popularized methods like Level Set-based representations, which map spatial coordinates to a signed distance function (SDF) (Park et al., 2019; Jiang et al., 2020; Yariv et al., 2020) or occupancy fields (Mescheder et al., 2019).

One of the most popular INR methods is the Neural Radiance Field (NeRF) (Mildenhall et al., 2021), an alternative implicit representation that directly maps spatial coordinates and viewing angles to local point radiance. NeRFs can also perform novel view synthesis through differentiable volumetric rendering, utilizing only RGB supervision and known camera poses. Furthermore, there have also been many extensions of NeRF-based methods for dynamic scenes (Pumarola et al., 2020; Gafni et al., 2020; Park et al., 2020), compression (Takikawa et al., 2022), editing (Liu et al., 2021; Jiakai et al., 2021; Liu et al., 2022), and more.

NeRFs in the wild. Applying NeRFs in uncontrolled environments often results in the emergence of artifacts, often referred to as *floaters*. These are small, disconnected regions in volumetric space that inaccurately represent parts of the scene when viewed from different angles, appearing as blurry clouds or distortions in the scene which we demonstrate in Figure 4. These artifacts are primarily observed under conditions such as sub-optimal camera registration (Warburg et al., 2023), sparse input sets (Liu et al., 2023; Warburg et al., 2023), strong view-dependent effects (Liu et al., 2023), and inaccuracies in scene geometry estimation. Additionally, the very nature of NeRF’s approach, which reconstructs scene geometry and texture from 2D projections of a 3D scene causes information loss.

To mitigate floater artifacts in NeRF reconstructions, several strategies focus on improving camera pose estimation and scene geometry. Mip-NeRF 360 (Barron et al., 2022) and



Figure 4: Floater artifacts often appear in NeRF-based models for casually-captured videos.

RegNeRF (Niemeyer et al., 2022) enhance alignment and consistency, with the former also incorporating a distortion loss to prevent floaters. Techniques such as Nerfbusters (Warburg et al., 2023) and ViP-NeRF (Somraj and Soundararajan, 2023) leverage visibility information to better reconstruct scenes with sparse data, while CleanNeRF (Liu et al., 2023) offers a method to separate view-dependent effects for more accurate geometry estimation. Additionally, previous works have also explored post-processing methods to remove floaters without modifying the original NeRF framework (Jambon et al., 2023; Wirth et al., 2023; Goli et al., 2023).

NeRFs for Medical Imaging. The application of NeRFs in medical imaging is confronted with unique challenges that stem from the inherent properties of medical imaging data and the demand for accurate representations. These include the need for detailed inner structure representation, the handling of ambiguous object boundaries, the significance of color density variations in medical images, and the adaptation to different imaging principles compared to traditional NeRF applications (Wang et al., 2024).

Recent advances have demonstrated that NeRF-based techniques, such as MedNeRF (Corona-Figueroa et al., 2022b) and UMedNeRF (Hu et al., 2024), as effective in reconstructing CT projections from single X-ray views, showcasing their potential to minimize exposure to ionizing radiation in medical imaging. ACNeRF (Sun et al., 2024) further enhances reconstruction quality through improved alignment and pose correction.

There have also been other specialized NeRFs either for a particular body part or a kind of imaging technique. In brain imaging, advances such as 3D reconstruction from MRI scans using NeRFs (Iddrisu et al., 2023) aim to improve diagnostics and patient care by providing more precise and less invasive diagnostic methods. Similarly, in dental and maxillofacial imaging, Masked NeRF (Zhou et al., 2023) has been introduced to address challenges related to skull CBCT reconstructions, offering refined methods to mitigate artifacts and improve pose estimation accuracy. For cardiovascular imaging, there has been work on 3D reconstruction of coronary angiography images (Zha et al., 2022; Maas et al., 2023) and improved diagnostic capabilities. Similarly, NeRF-based models have been developed for feet (Zha et al., 2022), chest CT imaging (Corona-Figueroa et al., 2022b; Hu et al., 2024; Sun et al., 2024; Maas et al., 2023), and abdominal surgical planning (Wang et al., 2022).

Furthermore, there has been similar work to ours, leveraging ultrasounds to perform 3D reconstruction. Particularly, there have been a few studies performing 3D reconstruction on

ultrasound images (Li et al., 2021b; Yeung et al., 2021; Gu et al., 2022; Song et al., 2022). Ultra-NeRF (Wysocki et al., 2024) is another popular technique that encodes the physics of ultrasound into volume rendering and demonstrates promising results for liver and spine ultrasounds. However, such methods still pose multiple challenges in adopting NeRF-based methods for ultrasounds. These methods qualitatively produce multiple ultrasound imaging artifacts, are unable to capture intricate details like tissue boundaries and all ultrasound imaging performed by clinicians inherently has some body motion in it which these methods do not account for. These limit such methods from being applied in the wild. However, our method, NeRF-US, tackles these challenges common across all current studies.

3. Preliminary

3.1. Diffusion Models

The denoising diffusion probabilistic model (DDPM) (Ho et al., 2020) in the forward process takes an input image $\mathbf{x}_0 \sim q(\mathbf{x}_0)$, and progressively in the T steps add Gaussian noise to the image. This is implemented using a Markov chain of T steps.

$$\begin{aligned} q(\mathbf{x}_t \mid \mathbf{x}_{t-1}) &= \mathcal{N}(\mathbf{x}_t; \mu_t = \sqrt{1 - \beta_t} \cdot \mathbf{x}_{t-1}, \beta_t \mathbf{I}) \\ &= \mathcal{N}(\mathbf{x}_t; \sqrt{\bar{\alpha}_t} \mathbf{x}_0, (1 - \bar{\alpha}_t) \mathbf{I}) \end{aligned} \quad (1)$$

At each step of the Markov chain, the forward process adds a Gaussian noise with variance β_t to \mathbf{x}_{t-1} , $\bar{\alpha}_t = \prod_{s=0}^t 1 - \beta_s$, β_t is a hyper-parameter representing a variance schedule, and produces a new latent variable \mathbf{x}_t . The reverse process of diffusion models aims to recover the data distribution from the Gaussian noises by approximating the posterior distribution $q(\mathbf{x}_{t-1} \mid \mathbf{x}_t, \mathbf{x}_0)$ as,

$$p_\theta(\mathbf{x}_{t-1} \mid \mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \mu_\theta(\mathbf{x}_t, t), \Sigma_\theta(\mathbf{x}_t, t)) \quad (2)$$

This only requires approximating the mean $\mu_\theta(\mathbf{x}_t, t)$ by training some neural network $\epsilon_\theta(\mathbf{x}_t, t)$, this network can be trained using the optimization objective,

$$\mathcal{L}_t = \mathcal{E}_{\mathbf{x}_0, t, \epsilon} \left[\left\| \epsilon - \theta(\sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon, t) \right\|^2 \right] \quad (3)$$

3.2. Neural Radiance Fields

Neural Radiance Fields (NeRFs) (Mildenhall et al., 2021) use a single 5-D coordinate as input (x, y, z, θ, ϕ) representing the spatial location and viewing angle, and outputs (r, g, b, σ) representing color intensities and volume density. NeRFs usually output different representations for the same point when viewed from different camera angles which allows us to capture various lighting effects as well. To train these networks without ground truth density and color, we sample pixels from the original images, using ray marching. For a given pixel we have the ray,

$$r(t) = o + td \quad (4)$$

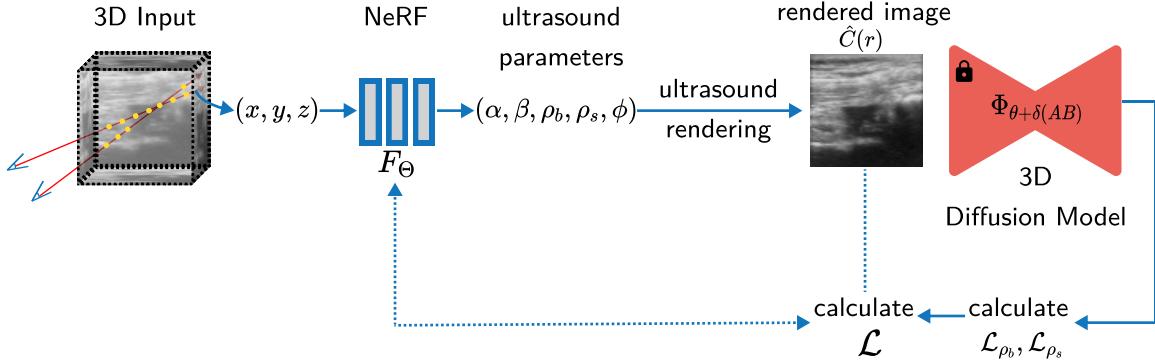


Figure 5: **An overview of how our method works.** We train a NeRF model (Section 4.2) that uses ultrasound rendering to convert the representations into a 2D image after which we infer through a 3D diffusion model (Section 4.1) which has geometry priors through which we calculate a modified loss definition to train the NeRF.

where o represents the origin and d the direction, which we can sample at timesteps t . To map these back to an image we can integrate these rays (differentiable rendering),

$$C(r) = \int_{t_n}^{t_f} \underbrace{T(t)}_{\text{transmittance}} \cdot \overbrace{\sigma(r(t))}^{\text{density}} \cdot \underbrace{c(r(t), d)}_{\text{color}} dt \quad (5)$$

We can now train the network by simply computing L_2 loss since from Equation (5) we have a way to map the neural field output back to a 2D image.

4. NeRF-US

Our goal is to produce a 3D representation given a set of ultrasound images taken in the ‘wild’ and their camera positions. Our approach on a high level involves modifying volumetric rendering while training NeRFs, and using a Diffusion Model to produce clean artifact-free representations as summarized in Figure 5. We show our approach for training the diffusion model (Section 4.1) and our approach on training the NeRF model (Section 4.2). Notice that, while our training approaches utilize data around the human knee, our work is not limited to this single application. It can be extended right out-of-the-box to any kind of medical ultrasound imaging. We limit our experiments to just the human knee to be able to collect sufficient data and to be able to evaluate our approach satisfactorily.

4.1. Training the Diffusion Model

The first step of our approach relies on the training of a 3D diffusion model, which can serve as geometric priors for our NeRF model (Section 4.2).

Similar to Nerfbusters (Warburg et al., 2023), this diffusion model produces an $32 \times 32 \times 32$ occupancy grid, x . We use the 3D diffusion model Φ with parameters θ trained

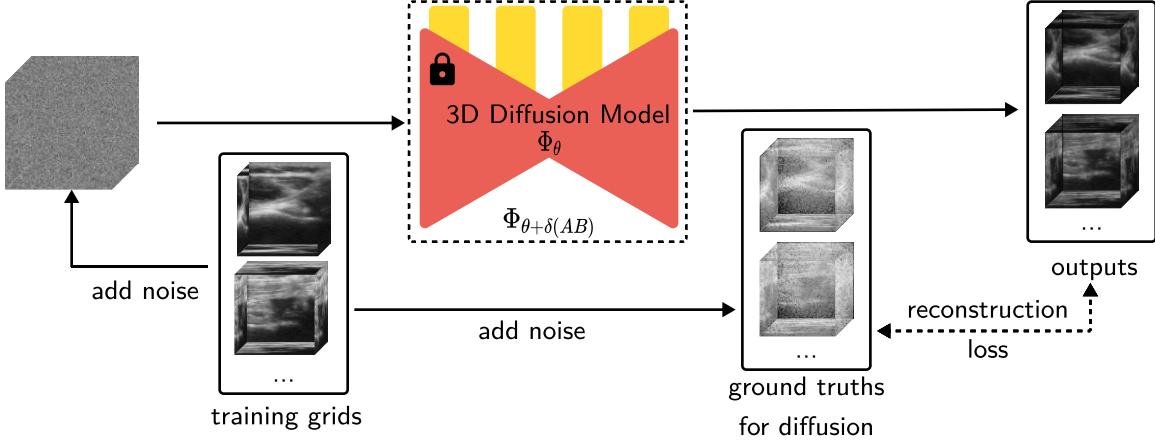


Figure 6: **Training our Diffusion Model.** An overview of how our diffusion model is finetuned, we use 32^3 -sized patches to LoRA-finetune a 3D diffusion model trained on ShapeNet (Chang et al., 2015).

on ShapeNet (Chang et al., 2015), from Nerfbusters (Warburg et al., 2023). Based on LoRA (Hu et al., 2022), our fine-tuning process now utilizes the same loss function as the original DDPM training, with the low-rank update applied to the model’s parameters,

$$\mathcal{L}_{\text{FT}} = \|x - \Phi_{\theta+\delta(AB)}(\bar{x}_t + (1 - \bar{\beta}_t), t)\|_2^2 \quad (6)$$

where x is the target occupancy grid, \bar{x}_t is the noised version of x at timestep t , δ is a scaling factor determining the magnitude of adaptation and AB represents a low-rank update to the original weights, and $\bar{\beta}_t$ controls the noise level as per the noise schedule. The model $\Phi_{\theta+\delta(AB)}$ indicates the fine-tuned model. We make sure to only update the parameters of A and B matrices are updated during this process, leaving the original model parameters θ fixed.

We finetune the 3D diffusion model on a small dataset of voxels around the human knee generated synthetically. From these synthetic knees, we extracted localized, cube-bounded patches that represent the area of interest for ultrasound imaging. We particularly ensure that all the voxels we sample have one of their ends on human skin mimicking ultrasound imaging conditions. These cubes are variably sized proportional to the knee model’s bounding volume and are voxelized and scaled. We finetune the model Φ as summarized in Figure 6, on these $32 \times 32 \times 32$ -sized voxels to produce an adapted model $\Phi_{\theta+\delta(AB)}$ which we use as our 3D geometric priors.

4.2. Training the NeRF

Following previous ultrasound representations (Salehi et al., 2015; Wysocki et al., 2024), the parameter vector for some position $q = (x, y, z)$ is $[\alpha(q), \beta(q), \rho_b(q), \rho_s(q), \phi(q)]$ where α is the attenuation, β is the reflectance, ρ_b is border probability, ρ_s is the scattering density, and ϕ is the scattering intensity. Just like standard NeRF models, we employ an MLP to

learn the mapping,

$$\mathbf{F}_\Theta : q \rightarrow [\alpha, \beta, \rho_b, \rho_s, \phi]$$

Ultra-NeRF (Wysocki et al., 2024) for the volume rendering defines the intensity as

$$I(r, t) = I_0 \cdot \prod_{n=0}^{t-1} [(1 - \beta(r, n)) \cdot G(r, n)] \cdot \exp \left(- \int_{n=0}^{t-1} (\alpha \cdot f \cdot dt) \right), \quad (7)$$

where $\beta(r, t)$ represents the reflection coefficient, I_0 represents the initial unit intensity, $G(r, t)$ represents a boundary mask, and $(\alpha f dt)$ represents the loss of energy due to attenuation at each step of the propagation with f as the frequency. Composing these intensities a 2D ultrasound image is generated which can be trained using the standard NeRF techniques.

We particularly modify this training process inspired by the area of work that incorporate diffusion models in the NeRF training (Wynn and Turmukhambetov, 2023; Warburg et al., 2023; Chen et al., 2023; Gu et al., 2023; Yang et al., 2023), however incorporating these with the rendering process is not straightforward. We do so leveraging the diffusion model we trained $\Phi_{\theta+\delta(AB)}$ to refine key ultrasound parameters: border probability ρ_b , scattering density ρ_s for which we can efficiently use the 3D geometric priors. Given a set of ultrasound parameters $\mathcal{G}_i = \{\rho_b, \rho_s\}$ for each voxel i , we process these through the diffusion model to generate predictions on the expected values of these parameters. We then denote the two new loss terms as,

$$\begin{aligned} \mathcal{L}_{\rho_b} &= \frac{1}{N} \sum_{i=1}^N |\mathcal{G}_i^{\rho_b} - m_i^{\rho_b}|^2 \\ \mathcal{L}_{\rho_s} &= \frac{1}{N} \sum_{i=1}^N |\mathcal{G}_i^{\rho_s} - m_i^{\rho_s}|^2, \end{aligned} \quad (8)$$

where ρ_b represents the border probability, ρ_s represents the scattering density, N represents the number of points being sampled, $m_i^{\rho_b}$ represents the value of ρ_b from the output of the diffusion model $\Phi_{\theta+\delta(AB)}$ for a voxel i , and $m_i^{\rho_s}$ represents the value of ρ_s from the output of the diffusion model $\Phi_{\theta+\delta(AB)}$ for a voxel i . We find that formulating the two loss components as shown in Equation (8) to perform particularly well since many of the underlying objects captured by ultrasound imaging can often contain opaque, translucent, and transparent in the same scene (note: that our voxels are rather small and often only contain a single kind of object).

We now write our final loss definition for the NeRF training as

$$\mathcal{L} = \underbrace{\sum_{\mathbf{r} \in \mathcal{R}} \left\| \hat{C}(\mathbf{r}) - C(\mathbf{r}) \right\|_2^2}_{\text{move output close to ground-truth image}} + \overbrace{\lambda_{\rho_b} \mathcal{L}_{\rho_b}}^{\text{move output close to correct border prob.}} + \overbrace{\lambda_{\rho_s} \mathcal{L}_{\rho_s}}^{\text{move output close to correct scattering dens.}} \quad (9)$$

where \mathcal{R} is the set of rays in a given batch, $\lambda_{\rho_b}, \lambda_{\rho_s}$ are the weighting factors, $C(\mathbf{r})$ is the ground truth frame, $\hat{C}(\mathbf{r})$ is the frame obtained after rendering which we get by Equation (7).

Method	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow
DCL-Net (Guo et al., 2020)	14.38 (± 0.89)	0.4418 (± 0.16)	0.5618 (± 0.17)
ImplicitVol (Yeung et al., 2021)	18.42 (± 0.83)	0.6182 (± 0.16)	0.5482 (± 0.06)
Original NeRF (Mildenhall et al., 2021)	14.90 (± 1.06)	0.5516 (± 0.03)	0.5371 (± 0.04)
Gu et al. (2022)	15.01 (± 1.13)	0.5724 (± 0.18)	0.5092 (± 0.07)
Instant-NGP (Müller et al., 2022)	22.73 (± 4.06)	0.7399 (± 0.11)	0.2842 (± 0.08)
TensoRF (Chen et al., 2022)	25.14 (± 6.16)	0.7548 (± 0.14)	0.2716 (± 0.11)
Nerfacto (Tancik et al., 2023)	15.04 (± 1.76)	0.4631 (± 0.05)	0.4645 (± 0.07)
Gaussian Splatting (Kerbl et al., 2023)	22.33 (± 4.59)	0.7746 (± 0.13)	0.2683 (± 0.10)
Ultra-NeRF (Wysocki et al., 2024)	24.14 (± 2.54)	0.8312 (± 0.15)	0.2573 (± 0.16)
Ours (NeRF-US)	27.37 (± 1.83)	0.8412 (± 0.13)	0.2325 (± 0.14)

Table 1: **Quantitative Results.** We show quantitative comparisons between our NeRF-US against the baselines of our model on our “Ultrasound in the wild” dataset. We report the average PSNR \uparrow , SSIM \uparrow , LPIPS \downarrow metrics across all scenes. The best, second best, and third best results for each metric are color coded.

It is also straightforward to notice that incorporating our approach does not require any overhead during inference. Furthermore, once the diffusion model is trained, there is very little overhead (caused by inferencing the diffusion model) while training the NeRF.

5. Experiments

5.1. Ultrasound in the wild Dataset

We collect the data following a standardized protocol using a hand-held ultrasound device (Butterfly iQ+ by Butterfly Network Inc., Burlington, MA, USA¹). We capture video and mid-sagittal images, including the suprapatellar longitudinal view of the suprapatellar recess of the knee. Using this, our pilot dataset captures 10 unique casual sweeps at 30 FPS on a subject around the human knee with at least 85 frames in each sweep. All sweeps in this dataset have been captured by the authors on healthy knees following institutional REB (Research Ethics Board) guidelines; we provide details about REB guidelines in Appendix D. Following this, the camera registration is performed by COLMAP (Schönberger et al., 2016; Schönberger and Frahm, 2016). To create testing frames, we use every 8th frame. A popular way to evaluate such models is to use another camera across a different trajectory to create the test frames, often with two imaging equipment attached to each other. However the nature of how ultrasounds are captured in the wild make it quite difficult to build a setup that could allow us to collect this data.

1. <https://www.butterflynetwork.com/iq-plus>

Method	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow
Original NeRF (Mildenhall et al., 2021)	21.36 (± 1.27)	0.5100 (± 0.12)	0.2415 (± 0.14)
Instant-NGP (Müller et al., 2022)	26.13 (± 1.35)	0.5052 (± 0.05)	0.2324 (± 0.06)
TensoRF (Chen et al., 2022)	27.16 (± 3.17)	0.5178 (± 0.03)	0.2342 (± 0.05)
Nerfacto (Tancik et al., 2023)	26.28 (± 2.63)	0.5124 (± 0.04)	0.2353 (± 0.04)
Gaussian Splatting (Kerbl et al., 2023)	29.72 (± 4.27)	0.5248 (± 0.12)	0.2214 (± 0.11)
Ultra-NeRF (Wysocki et al., 2024)	28.12 (± 2.35)	0.5314 (± 0.09)	0.2182 (± 0.10)
Ours (NeRF-US)	29.24 (± 2.13)	0.5306 (± 0.05)	0.1963 (± 0.13)

Table 2: **Quantitative Results.** We show quantitative comparisons between our NeRF-US against the baselines of our model on the “phantom” dataset from Wysocki et al. (2024). However, the captures in this dataset are not in the wild. We report the average PSNR \uparrow , SSIM \uparrow , LPIPS \downarrow metrics across all scenes. The best, second best, and third best results for each metric are color coded.

5.2. Experimental Setup

We evaluate the performance of our approaches based on the novel view synthesis quality on the “Ultrasound in the wild” Dataset (human knee) we introduced in Section 5.1 and the “phantom dataset” (human spine) (Wysocki et al., 2024). The generated images are compared with the ground truth test view images to calculate a few commonly used quantitative metrics that have become the standard way to evaluate NeRFs: PSNR, MS-SSIM (Wang et al., 2003), and LPIPS (Zhang et al., 2018). We report the average values of these quantitative metrics across multiple frames, we follow the evaluation from most previous techniques (Mildenhall et al., 2021). We compare our model with the baseline models of ImplicitVol (Yeung et al., 2021), Gu et al. (2022), DCL-Net (Guo et al., 2020), Ultra-NeRF (Wysocki et al., 2024), as well as with standard NeRF methods: Original NeRF (Mildenhall et al., 2021), Instant-NGP (Müller et al., 2022), TensoRF (Chen et al., 2022) and Nerfacto (Tancik et al., 2023). We also compare our method with standard Gaussian Splatting (Kerbl et al., 2023). We provide more details about the implementation in Appendix A.

5.3. Results and Discussion

Quantitative Results. We demonstrate the quantitative results of our approach against other methods for novel views on our “Ultrasound in the wild” dataset. We compare our approach quantitatively across methods that are specialized for 3D ultrasound reconstruction as well as state-of-the-art standard 3D reconstruction methods which are not specific to ultrasound or medical imaging. We particularly compare with state-of-the-art 3D reconstruction methods which are not focused on ultrasound to demonstrate our approach’s significance for reconstruction such sound-based imaging. We show these quantitative results and comparisions in Table 1 and Table 2. We also demonstrate the quantitative results

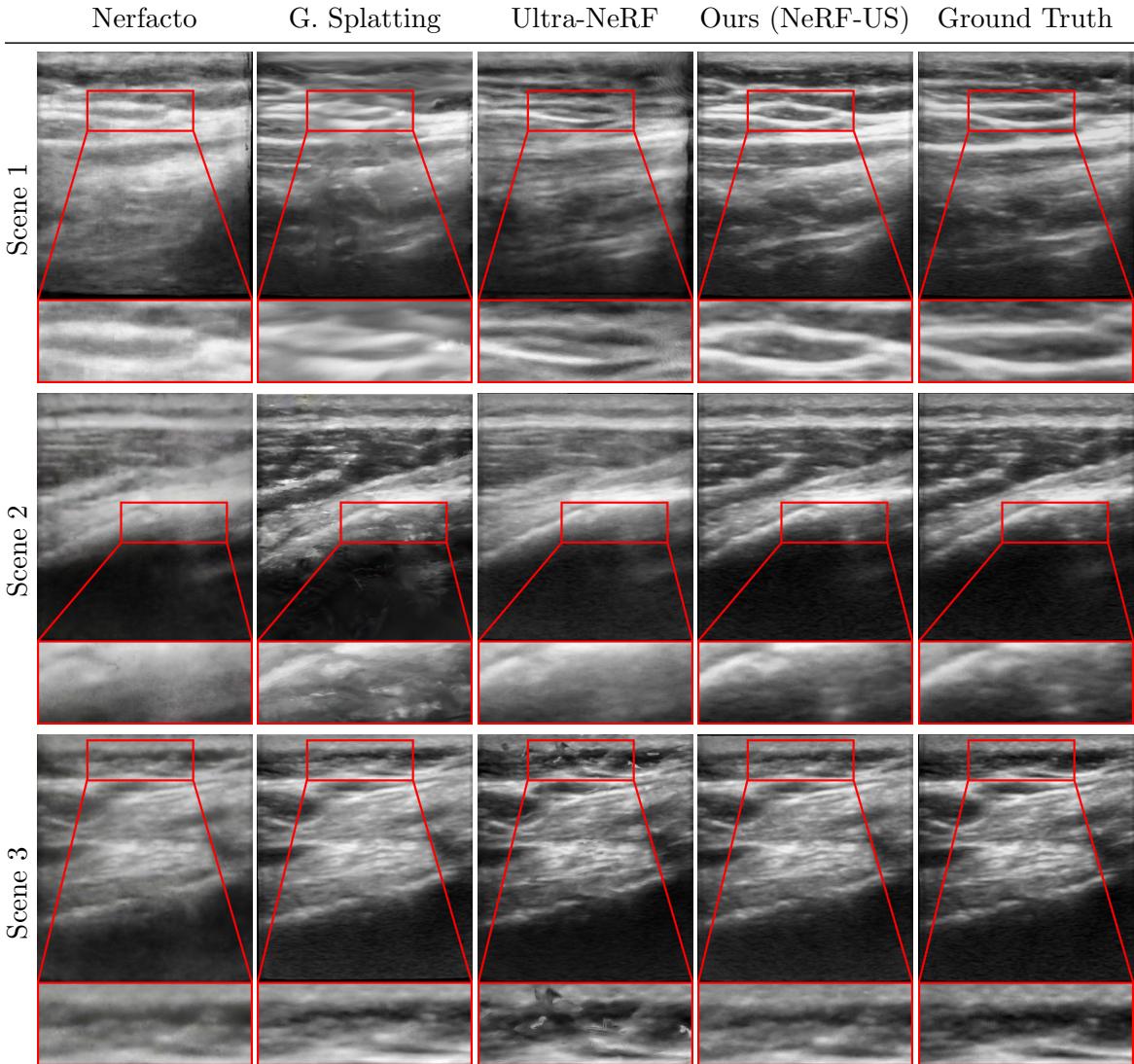


Figure 7: **Qualitative Results.** We demonstrate the results of our method and compare it qualitatively with Nerfacto (Tancik et al., 2023), Gaussian Splatting (Kerbl et al., 2023), and Ultra-NeRF (Wysocki et al., 2024). Our approach, NeRF-US, produces accurate and high-quality reconstructions as compared to the baseline models on novel views (**best viewed with zoom**).

on the “phantom” dataset (Wysocki et al., 2024). However, this dataset does not feature in the wild captures.

Qualitative Results. We present the qualitative results of novel view synthesis in Figure 7. We particularly show that other approaches tend to reconstruct ultrasound scenes with severe geometric artifacts. The rendered ultrasound scenes are blurry or torn apart

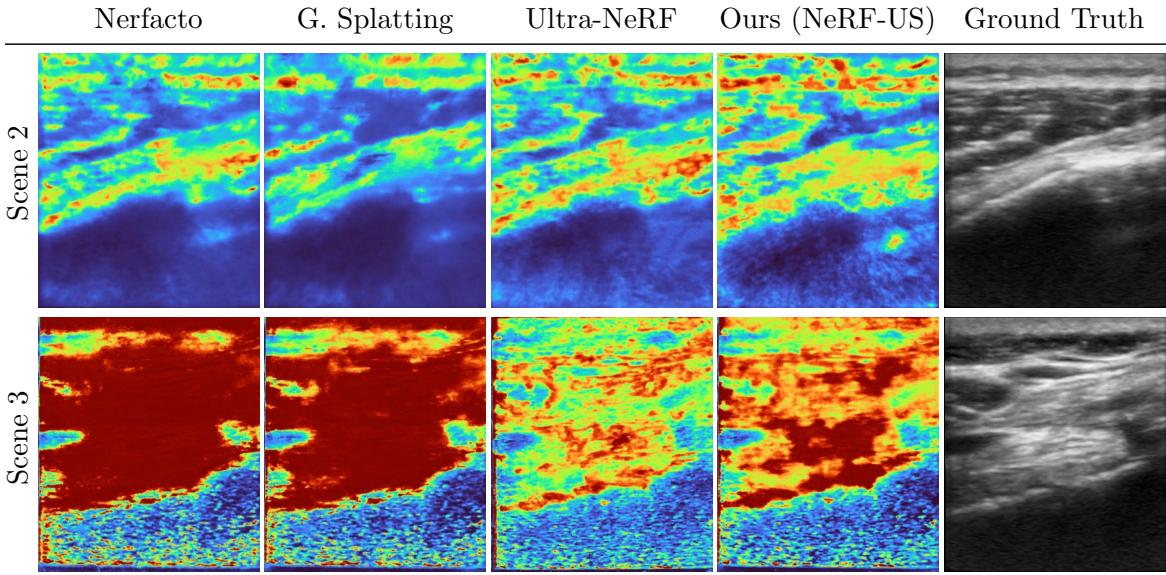


Figure 8: **Qualitative Results.** We demonstrate the results of depth maps produced from our method and compare them qualitatively with Nerfacto (Tancik et al., 2023), Gaussian Splatting (Kerbl et al., 2023), and Ultra-NeRF (Wysocki et al., 2024) (**best viewed in color and with zoom**).

along the moving trajectory. We particularly also notice that other approaches especially Ultra-NeRF (Wysocki et al., 2024) produce reconstructions where tissue borders and separation are not captured properly due to a lot of uncertainty in these areas by all previous approaches. We also demonstrate some of these issues in Figure 8. Our approach particularly alleviates these issues with the reconstruction of 3D ultrasound representations.

5.4. Ablations

We provide an in-depth analysis motivating our two-fold training approach highlighted in Section 4 by ablating each component and evaluating the use of each component. We provide ablations in Figure 9 and Table 3.

Border Probability Guidance (w/o \mathcal{L}_{ρ_b}). To implement this we simply set λ_{ρ_b} to 0 for the entire training process in Equation (9). We find that the border probability guidance is useful for accurately modeling tissue interface locations and border locations; if we disable it during training, we observe that many objects blend into each other and have discontinuities in the representation space.

Scattering Density Guidance (w/o \mathcal{L}_{ρ_s}). To implement this we simply set λ_{ρ_s} to 0 for the entire training process in Equation (9). We find that the scattering density guidance is useful to accurately model bodily objects; if we disable it during the training, we observe that many microstructural features are missing from the reconstructions. For example,

Method	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow
Ultra-NeRF (Wysocki et al., 2024)	24.14 (± 2.54)	0.8312 (± 0.15)	0.2573 (± 0.16)
Ours (NeRF-US)	27.37 (± 1.83)	0.8412 (± 0.13)	0.2325 (± 0.14)
<i>Ablation Study</i>			
Ours (NeRF-US)			
w/o \mathcal{L}_{ρ_b}	24.89 (± 1.72)	0.8208 (± 0.98)	0.2613 (± 0.13)
w/o \mathcal{L}_{ρ_s}	26.02 (± 1.67)	0.8197 (± 1.10)	0.2598 (± 0.08)
w/o $I(t)$	23.98 (± 1.46)	0.8065 (± 1.23)	0.2591 (± 0.11)

Table 3: **Ablation Study.** We show ablations of our approach: w/o \mathcal{L}_{ρ_b} , w/o \mathcal{L}_{ρ_s} , and w/o the rendering $I(t)$. The best, second best, and third best results for each metric are color coded.

in Figure 9, many minute details are entirely missing when we do not use scattering density guidance.

Ultrasound Rendering (w/o $I(t)$). Technically, learning a NeRF model without the ultrasound rendering (Equation (7)) is possible, to implement this we still calculate the rendered 2D image with ultrasound rendering since the results from this are used to calculate \mathcal{L}_{ρ_b} and \mathcal{L}_{ρ_s} terms, however, we parallelly also learn another model which is trained with the objective function as Equation (9) but uses standard volumetric rendering to calculate $\hat{C}r$ and we report the metrics for this NeRF model. We find that using ultrasound rendering is useful to model ultrasound effects on the image; if we disable it during the training, we observe that while individual frames look decently reconstructed, the 3D geometry of the underlying objects is improper due to the nature of how ultrasounds capture data.

6. Limitations

Although our method produces compelling reconstructions of ultrasound imaging, there are several limitations and avenues for future work. First, the complexity of motion in our scenes is limited to simple movements, while our approach is accurately able to reconstruct ultrasounds taken in the natural setting which always has some movement, our method fails to reconstruct accurately when there are immensely complex full-body motions. We believe that our method will directly benefit from the progress on dynamic reconstruction methods that use dynamic representations eg. HyperNeRF (Park et al., 2021), NeRF-DS (Yan et al., 2023), Dynamic 3D Gaussians (Luiten et al., 2023). Moreover, currently our diffusion model is fine-tuned on voxels specific to a body region, while fine-tuning the diffusion model is very cheap (< 5 hours on A100-80), and we believe that an interesting avenue for future work would be to build a generalized diffusion model. Lastly, our diffusion model is fine-tuned on a dataset of synthetic voxels (notice that our NeRF model is evaluated and trained on real-life data only), and we currently do not experiment with a real-life dataset from 3D captures. Furthermore, an interesting avenue for future works is to explore the effect

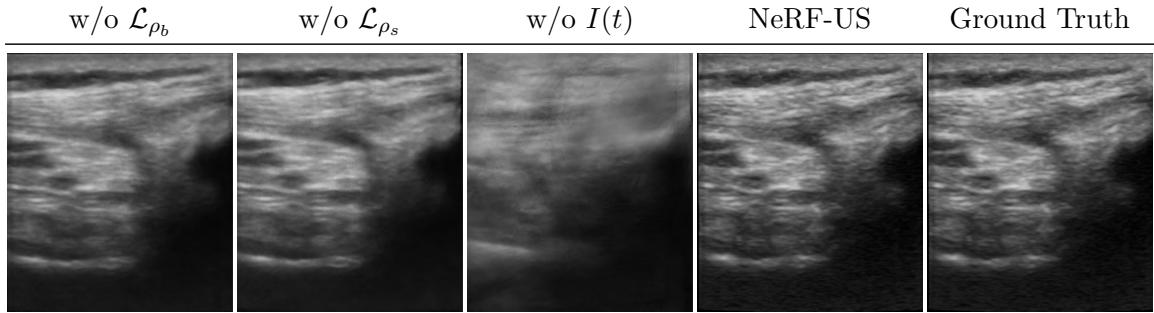


Figure 9: **Ablation Study.** We assess the qualitative impact of removing each of the components of our pipeline: \mathcal{L}_{ρ_b} , \mathcal{L}_{ρ_s} , and $I(t)$. Our approach without the border probability guidance (\mathcal{L}_{ρ_b}) fail to reconstruct minor details in the scene especially it is unable to clearly segregate multiple objects in the image. Removing the scattering density guidance (\mathcal{L}_{ρ_s}) produces very blurred reconstructions. Our approach without the ultrasound rendering produces a lot of artifacts in the reconstruction and fails to capture most aspects of the reconstruction. (**Best viewed with zoom**).

of training the diffusion model with other modalities, we particularly believe it might be promising to explore training the diffusion model on Magnetic Resonance Imaging (MRI) scans to reconstruct ultrasound imaging.

7. Conclusion

Our work builds a NeRF-based technique that can perform accurate view synthesis and 3D reconstruction on ultrasound imaging. Our work is the first to tackle the problem of performing view synthesis and 3D reconstructions on ultrasound imaging data collected in its natural in the wild form as opposed to works that tackle this problem on simulated data or very heavy ultrasound capture mechanisms. We also observe accurate artifact-free outputs for ultrasound imaging with our method. We will release the code and data to facilitate future research in this area.

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Appendix A. Implementation Details

A.1. Training the Diffusion Model

The pre-trained diffusion model is a UNet-based diffusion model designed for $32 \times 32 \times 32$ data cubes. The model utilizes 3D convolutions with a base channel count of 32, employing channel multipliers of (1, 2, 4, 8) across resolution levels. We use two residual blocks per resolution level, with self-attention mechanisms strategically applied at $16\times$ and $8\times$ downsampling. The model also incorporates time embeddings. The model features a down-sampling path that progressively reduces spatial dimensions while increasing channel count, a bottleneck with residual connections and attention mechanisms, and an upsampling path with skip connections. The pre-trained model also uses scale conditioning through a learned embedding.

We provide more details on how we perform LoRA (Hu et al., 2022) adaption to the denoising diffusion model. Our implementation closely follows the original LoRA, which demonstrated the adaption approach for language models, and draws inspiration from the HuggingFace Diffusers implementation, which demonstrates adaption for text-to-image (T2I) models.

We use the 3D diffusion model Φ with parameters θ trained on ShapeNet (Chang et al., 2015) which works on $32 \times 32 \times 32$ occupancy grid, x , from Nerfbusters (Warburg et al., 2023). Based on LoRA (Hu et al., 2022), for a given layer in Φ , we introduce trainable low-rank matrices. For the weight matrix $W \in \mathbb{R}^{d_{\text{out}} \times d_{\text{in}}}$ in the model, LoRA decomposes the adaptation into two low-rank matrices, $A \in \mathbb{R}^{d_{\text{out}} \times r}$ and $B \in \mathbb{R}^{r \times d_{\text{in}}}$, where $r \ll \min(d_{\text{out}}, d_{\text{in}})$ representing the rank controlling adaption. The updated weights W' can be computed as,

$$W' = W + \delta(AB) \quad (10)$$

where δ is a scaling factor that determines the magnitude of the adaptation and AB represents a low-rank update to the original weights.

Our fine-tuning process now utilizes the same loss function as the original DDPM training, with the low-rank update applied to the model parameters, giving us Equation (6).

A.2. NeRF Optimization Objective

Our optimization objective for the NeRF was defined in Equation (9), we can write this optimization objective as,

$$\begin{aligned} \mathcal{L} &= \sum_{\mathbf{r} \in \mathcal{R}} \overbrace{\left\| \hat{C}(\mathbf{r}) - C(\mathbf{r}) \right\|_2^2}^{\text{photometric loss}} + \lambda_{\rho_b} \mathcal{L}_{\rho_b} + \lambda_{\rho_s} \mathcal{L}_{\rho_s} \\ &= \sum_{\mathbf{r} \in \mathcal{R}} \left\| \hat{C}(\mathbf{r}) - C(\mathbf{r}) \right\|_2^2 + \lambda_{\rho_b} \left(\frac{1}{N} \sum_{i=1}^N |C(i)^{\rho_b} - \Phi_{\theta+\delta(AB)}(C(i))^{\rho_b}|^2 \right) \\ &\quad + \lambda_{\rho_s} \left(\frac{1}{N} \sum_{i=1}^N |C(i)^{\rho_s} - \Phi_{\theta+\delta(AB)}(C(i))^{\rho_s}|^2 \right) \end{aligned} \quad (11)$$

We can notice that while our loss formulation is different than the Density Score Distillation Sampling (Warburg et al., 2023), however it can be still looked upon as adding a regularizer to the original NeRF photometric loss that penalizes an incorrect border probability and scattering density. Unlike Ultra-NeRF (Wysocki et al., 2024), we do not use a SSIM loss, we observe that with the new definition of \mathcal{L} , using the SSIM loss does not demonstrate any benefits over using the photometric loss term. Furthermore, we also observe that setting $\lambda_{\rho_b} > \lambda_{\rho_s}$ usually works well towards reconstructing high-quality scenes.

A.3. NeRF MLP

Following previous work on NeRFs like mip-NeRF (Barron et al., 2022), we use an MLP (F_Θ) with 8 layers and 256 hidden layer units with ReLU and a skip connection between the input and the fifth layer. To ensure numerical stability and physiologically plausible results, we enforce the attenuation parameter to assume continuous positive values, while reflectance, border probability, scattering density, and scattering intensity are confined within the range of $[0, 1]$. We do not employ additional MLP directional components for camera viewing directions (θ, ϕ) . This decision stems from the recognition that our MLP, does not directly assimilate information from the camera viewing angles. Rather, this aspect is effectively addressed by the ultrasound rendering of the reconstruction pipeline. Following NeRF (Mildenhall et al., 2021), we also use positional encodings to train the MLP.

A.4. Training Hyperparameters

All of our final code was optimized for a 1 x A100-80 GB GPU. For our Diffusion model, we trained our model for $30K$ steps with a batch size of 32 on the $32 \times 32 \times 32$ resolution. We use the Adam optimizer (Kingma and Ba, 2017) with $\beta_1 = 0.9$, $\beta_2 = 0.999$, and $\epsilon = 10^{-8}$ with an initial learning rate of 10^{-4} . We use cosine decay for the learning rate. We use a rank of 4 for the LoRA update weights. Our NeRF implementation is based upon Nerfstudio (Tancik et al., 2023). We trained our model for $300K$ iterations with a batch size of 2^{12} . We use the RAdam optimizer (Liu et al., 2020) with $\beta_1 = 0.9$ and $\beta_2 = 0.999$. We use a learning rate that starts at 5×10^{-4} and decays exponentially to 5×10^{-5} , and $\epsilon = 10^{-8}$. We however, notice that the results become pretty accurate after the first $100K$ iterations.

A.5. Code and Data

To foster future work in this direction we open-source our code and Ultrasound in the wild dataset which can be found on our project page at: rishitdagli.com/nerf-us/.

A.6. Baseline Models

Here we share the details for the baseline models we compare our approach with in Table 1. Our baseline models for Original NeRF (Mildenhall et al., 2021), Instant-NGP (Müller et al., 2022), TensoRF (Chen et al., 2022), Nerfacto (Tancik et al., 2023), and Gaussian Splatting (Kerbl et al., 2023) are trained with Nerfstudio (Tancik et al., 2023) implementations using the details we list below. Just like rest of our code all of our baseline models were trained on 1 x A100-80 GB GPU.

DCL-Net. We trained this baseline model for 300 epochs with a batch size of 2^5 using the Adam optimizer (Kingma and Ba, 2017) with $\beta_1 = 0.9$, $\beta_2 = 0.999$, and $\epsilon = 10^{-14}$. We use cosine decay starting with the learning rate of 5×10^{-5} and a warmup of 5 epochs. Furthermore, all the underlying images are resized to 224×224 -sized image.

ImplicitVol. We construct this baseline model with an MLP of 5 layers with 128 neurons. We trained this baseline model for $10K$ epochs and also use NeRF-style positional encodings. Since using this technique involves first estimating 2D plane locations, as suggested by ImplicitVol in their work we first estimate these plane positions using PlaneInVol (Wang et al., 2021). We use the Adam optimizer (Kingma and Ba, 2017) with $\beta_1 = 0.9$, $\beta_2 = 0.999$, and $\epsilon = 10^{-8}$ with an initial learning rate of 10^{-3} . We use the standard multi-step schedule with each of its stages at every 10 epochs with $\gamma = 0.9954$. We incorporate a window size of $k = 5$ for calculating the SSIM loss.

Original NeRF. We trained this baseline model for $300K$ iterations with a batch size of 2^{12} . We use the RAdam optimizer (Liu et al., 2020) with $\beta_1 = 0.9$ and $\beta_2 = 0.999$. We use a learning rate that starts at 5×10^{-4} and decays exponentially to 5×10^{-5} , and $\epsilon = 10^{-8}$. We also use gradient scaling to ensure that gradients near the camera are scaled down. We also use hierarchical sampling with 64 coarse samples and 128 importance samples for fine field evaluation. We use the NeRF defaults for all other hyperparamters.

Gu et al. (2022). We trained this baseline model for $20K$ iterations with a batch size of 2^2 . We use the Adam optimizer (Kingma and Ba, 2017) with an initial learning rate of 10^{-4} , $\epsilon = 10^{-8}$, $\beta_1 = 0.9$, $\beta_2 = 0.999$ and a meta learning rate of 10^{-5} . We also use LookAhead with 10 steps. We use an $\omega = 240$ for the SIREN activation. We use the defaults from Gu et al. (2022) for all other hyperparamters.

Instant-NGP. We trained this baseline model for $30K$ iterations with a batch size of 2^{12} . We use the Adam optimizer (Kingma and Ba, 2017) with $\beta_1 = 0.9$ and $\beta_2 = 0.999$. We use an initial learning rate of 10^{-2} and $\epsilon = 10^{-15}$. We exponentially decay the learning rate from 10^{-2} to 10^{-4} and use no warmup. We use a grid resolution of 128 with 4 grid levels for the multiresolution hash encoding. We also use a resolution of 2^{11} for the hashmap used by the MLP. We perform the sampling from the rays in between $[5 \times 10^{-2}, 10^3]$. We use the Instant-NGP defaults for all other hyperparamters.

TensoRF. We trained this baseline model for $30K$ iterations with a batch size of 2^{12} . We use the Adam optimizer (Kingma and Ba, 2017) with $\beta_1 = 0.9$ and $\beta_2 = 0.999$. We use an initial learning rate of 10^{-2} and $\epsilon = 10^{-8}$. We exponentially decay the learning rate from 10^{-3} to 10^{-4} and use no warmup. We also use TV regularization while training the field. We use the TensoRF defaults for all other hyperparamters.

Nerfacto. We trained this baseline model for $30K$ iterations with a batch size of 2^{12} . We use the Adam optimizer (Kingma and Ba, 2017) with $\beta_1 = 0.9$ and $\beta_2 = 0.999$. We use an initial learning rate of 10^{-2} and $\epsilon = 10^{-15}$. We exponentially decay the learning rate from 10^{-2} to 10^{-4} and use no warmup. We use a vector with 6 parameters representing $SO3 \times R3$ map for the camera optimizer. We use the Nerfacto defaults for all other hyperparamters.

Gaussian Splatting. We trained this baseline model for $30K$ iterations with a batch size of 2^{12} . We use the Adam optimizer (Kingma and Ba, 2017) with $\beta_1 = 0.9$ and $\beta_2 = 0.999$

for the Gaussian means network. For the Gaussian means network exponentially decay the learning rate from 1.6×10^{-4} to 1.6×10^{-6} , and $\epsilon = 10^{-15}$. We set the threshold for frustum culling Gaussians to 5×10^{-3} . For rendering we use the EWA volume splatting with a $[0.3, 0.3]$ screen space blurring kernel. Following recent popular work with Gaussian Splatting, we also apply a regularization loss when the ratio of a Gaussian’s maximum to minimum scale exceeds a threshold. We use the Gaussian Splatting defaults for all other hyperparamters.

Ultra-NeRF. We trained this baseline model for $100K$ iterations with a batch size of 2^{12} . We use the Adam optimizer (Liu et al., 2020) with $\beta_1 = 0.9$ and $\beta_2 = 0.999$. We use a learning rate that starts at 10^{-4} and decays exponentially in $250K$ steps with a decay of 0.1, and $\epsilon = 10^{-8}$. For the loss calculation we use a window size of $k = 7$ and $\lambda = 0.7$. We use the NeRF defaults for all other hyperparamters.

Appendix B. Evaluation Metrics

To evaluate the quality of our rendered images, we employ three standard metrics commonly used in the assessment of such models.

PSNR quantifies the ratio between the maximum possible signal power and the power of distorting noise, with higher values indicating better reconstruction quality.

SSIM evaluates the perceived quality of images by considering structural information changes, with values closer to 1 indicating higher similarity.

LPIPS is a perceptual metric leveraging deep neural networks trained on human judgments, aims to capture perceptual similarities between image patches, with lower scores indicating greater perceptual similarity.

Appendix C. Additional Qualitative Results

We present additional qualitative results reconstructed using our method on the Ultrasound in the wild dataset we introduced and show novel views in Figure 10. Furthermore, we encourage the reader to visit our project website for rendered videos with the camera moving around the scene in azimuth with a fixed elevation angle.

Appendix D. Ethics Statement

Our approach produces very compelling qualitative and quantitative results for reconstructing ultrasound imaging in the wild. However, in its current form, the authors do not give any theoretical guarantees while using this method and we strongly suggest readers looking to adopt this method to go through the limitations as well. Our data was collected with appropriate institutional guidelines on using medical data from humans. We obtained a waiver from our institution’s Research Ethics Board, as all data collected was part of a self study (PNT) for this proof of concept.

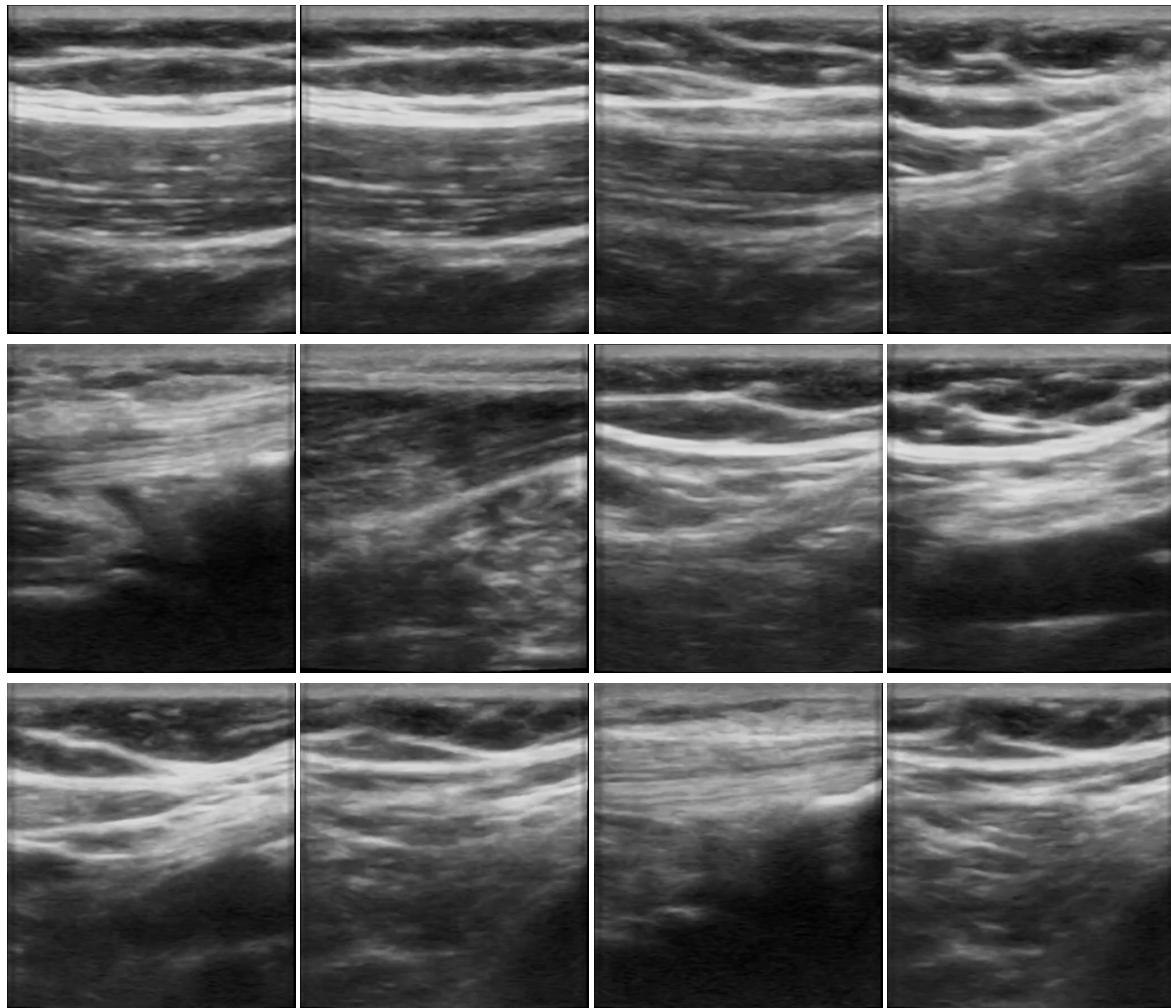


Figure 10: We present additional results using NeRF-US. In general, we observe high-quality artifact free reconstructions with our approach.