Ultra-NeRF: Neural Radiance Fields for Ultrasound Imaging

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Abstract

We present a physics-enhanced implicit neural representation (INR) for ultrasound (US) imaging that learns tissue properties from overlapping US sweeps. Our proposed method leverages a ray-tracing-based neural rendering for novel view US synthesis. Recent publications demonstrated that INR models could encode a representation of a three-dimensional scene from a set of two-dimensional US frames. However, these models fail to consider the view-dependent changes in appearance and geometry intrinsic to US imaging. In our work, we discuss direction-dependent changes in the scene and show that a physics-inspired rendering improves the fidelity of US image synthesis. In particular, we demonstrate experimentally that our proposed method generates geometrically accurate B-mode images for regions with ambiguous representation owing to view-dependent differences of the US images. We conduct our experiments using simulated B-mode US sweeps of the liver and acquired US sweeps of a spine phantom tracked with a robotic arm. The experiments corroborate that our method generates US frames that enable consistent volume compounding from previously unseen views. To the best of our knowledge, the presented work is the first to address view-dependent US image synthesis using INR.

Keywords: ultrasound, neural radiance fields, implicit neural representation

1. Introduction

3D visualization of an anatomy significantly improves our understanding of the underlying pathology, however, most US machines used in practice deliver only a single cross-sectional view of an anatomy at a time. Sonographers, through extensive training and clinical expertise, fuse these 2D scans into a 3D model in their minds. The anisotropic nature of US imaging contributes to the increased difficulty of this task. Since an image of a specific region in the patient's body depends on the probe position, a mental 3D model is constantly updated with images that may carry contradicting information for the same region. Nevertheless, a trained operator approaches this problem effortlessly owing to the consciousness of the anatomy and the effect of a probe position on its 2D representation. However, this manual visual analysis remains expensive and error-prone. A system that can reconstruct an US volume could reduce the cost of US acquisition and error rate.

Much research has recently been devoted to utilizing 3D US in diagnostic applications, as well as interventional radiology. 3D US volumes are conventionally generated using special wobbler probes, 2D transducers, or tracked probes to compound a 3D volume from 2D slices (Busam et al., 2018). In the last decade, new approaches such as computational sonography (Hennersperger et al., 2015), sensorless 3D US (Prevost et al., 2017), and deep learning-based image formation techniques (Simson et al., 2018) have aimed at improving the 3D compounding quality of this portable and affordable modality. Our proposed approach focuses on learning the 3D structure of an anatomy using 2D US images scanned

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from different viewpoints. This method enables us to generate isotropic 3D US volumes and introduces a new implicit 3D US representation for the medical image processing community to explore.

Although viewing-direction dependency is a prominent characteristic of US imaging, it is not a unique property of US. To some extent, a similar phenomenon characterizes natural images. For instance, since the non-Lambertian assumption does not hold for most real world objects, appearance due to reflections might be inconsistent between views (Gao et al., 2022). 3D scene reconstruction from a set of 2D view-dependent observations has been hence extensively studied (Seitz and Dyer, 1999; Niemeyer et al., 2020). An important aspect of any reconstruction method is a scene representation, which can be either explicit (e.g. volumetric grids), or implicit (e.g. implicit functions). Implicit scene representations, such as (truncated) signed distance functions ((T)SDFs) (Newcombe et al., 2011) represent a 3D scene as a function. Since neural networks are universal function approximators, they can be used to parametrize an implicit representation (Tewari et al., 2022). This fact has been a basis of a recent development in neural volumetric representation. In particular, Neural Radiance Field (NeRF) emerged as a new, potent method for generating photorealistic, view-dependent images of a static 3D scene from a collection of pose-annotated images (Mildenhall et al., 2022). In computer vision, NeRF became a baseline for for various research directions such as dynamic scenes (Park et al., 2021), large scale scenes (Rematas et al., 2022), or scene generalization (Yu et al., 2021). Moreover, as presented in iNeRF (Yen-Chen et al., 2021) representing a 3D model as a neural network provides a reference for 6DoF pose estimation, which potentially can find an application in US tracking. The idea behind NeRF, however, was primarily developed for the purpose of natural image synthesis and takes advantage of established methods from computer graphics.

In this paper, we propose an implicit neural representation for US exemplified with NeRF that facilitates the synthesis of B-mode images from novel viewpoints. Our contributions are as follows:

- a method that synthesises accurate B-mode images by learning the view-dependent appearance and geometry of a scene from multiple US sweeps;
- a physically sound rendering formulation based on a ray-tracing model, which considers the isotropic tissue characteristics important to US;
- open source datasets[1] comprising multiple tracked 2D US sweeps with highly accurate pose annotations and different viewpoints.

In our experiments, we use synthetic liver and spine phantom data. We evaluate our method quantitatively and qualitatively. In particular, we reason about the shortcomings of learning geometry without taking into account the rendering based on the physics behind US. To the best of our knowledge, this paper presents a new implicit neural representation for US that for the first time considers the anisotropic characteristics of US.

1. The link to the data and implementation will be provided upon acceptance.

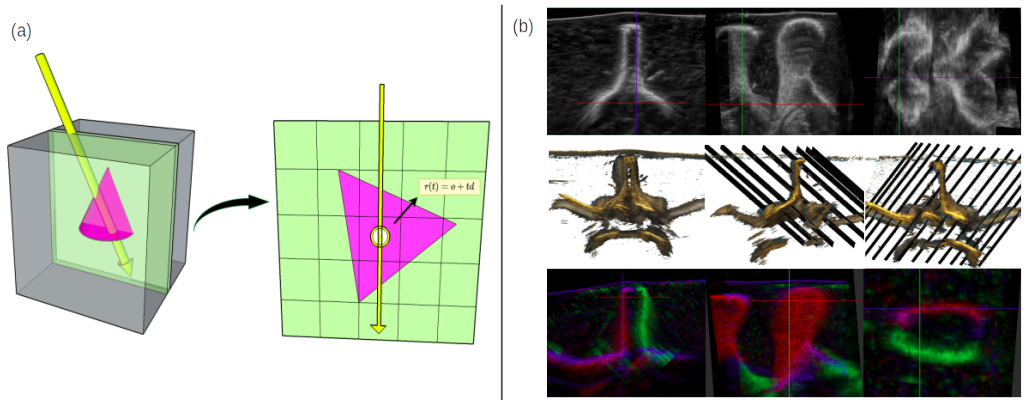

Figure 1: a) Each ray r corresponds to a single scan-line with origin $\mathbf{o}$ at top of the image plane and direction $\mathbf{d}$ pointing along the scan-line. Query points are defined by their spatial location $\mathbf{r}(t) = \mathbf{o}+t\mathbf{d}$.b) White intensities are the result of max-value compounding of images from all available angles. Red/Blue/Green intensities show the composition of the white intensities based on their view angle.

2. Related Work

Implicit representations in the form of (T)SDFs have been used for implicit geometric reconstruction (Newcombe et al., 2011). Recently, INR has been proposed to express signals as a neural network (Sitzmann et al., 2020) which can be seen as a universal function approximator, which represents a scene as a continuous function parameterised by its weights. As a consequence, it allows for a mapping from a 3D continuous coordinate space to intensity to store information about a 3D scene. As presented by Gu et al. (2022), we can exploit INR models to represent a 3D US volume learnt from a set of 2D US images. However, parametrizing an US volume using a 3D continuous coordinate space does not address a viewing direction impact on the observation. The progress in neural continuous shape representation sparked interest in their application to photorealistic novel view synthesis. In particular, in a seminal work introducing NeRF (Mildenhall et al., 2022), the authors propose a framework that combines neural representation of a scene and fully differentiable volumetric rendering. In NeRF, the representation of a scene is expressed by a fully-connected neural network. The network maps a 5D vector (a spatial location $\mathbf{x}$ and viewing direction $\mathbf{d}$) to volume density σ, and radiance $\mathbf{c}$. To learn this mapping a per-pixel camera ray is defined as $\mathbf{r}(t) = \mathbf{o} + t\mathbf{d}$ with the camera origin $\mathbf{o}$ in the center of the pixel defining the near plane. The final colour value of each pixel is defined by following formulas:

$$C(\mathbf{r}) = \int_{t_n}^{t_f} T(t)\sigma(t)c(t)dt \tag{1}$$

$$\text{where } T(t) = \exp - \int_{t_n}^{t_f} \sigma(\mathbf{r}(s))ds \tag{2}$$

The volume rendering integral in Equation (1) accumulates a radiance field along a ray, therefore each sampled position contributes to the final colour of a pixel. The input of each sample is controlled by the transmittance factor $T(t)$ (Equation (2)). Finally, the rendered pixel value is compared with a value in an image using a photometric loss.

Since its introduction, NeRF-based methods have demonstrated impressive results in various fields including medical imaging. For instance, MedNeRF propose a NeRF framework to reconstruct CT-projections from X-ray (Corona-Figueroa et al., 2022), and EndoNeRF adopts NeRF for surgical scene 3D reconstruction (Wang et al., 2022). Yet, surprisingly little investigation has been done to explore the potential of neural volumetric implicit representations for medical US. One of a few studies (Yeung et al., 2021; Gu et al., 2022; Song et al., 2022) focuses on reconstruction of a spine using the NeRF algorithm (Li et al., 2021). In this paper, the authors demonstrate that NeRF can render high-quality US images. However, they apply NeRF without considering a volumetric rendering method, which respects US physics. To address this shortcoming, we reformulate the rendering step to include the underlying US physics and incorporate it into the NeRF framework.

3. Method

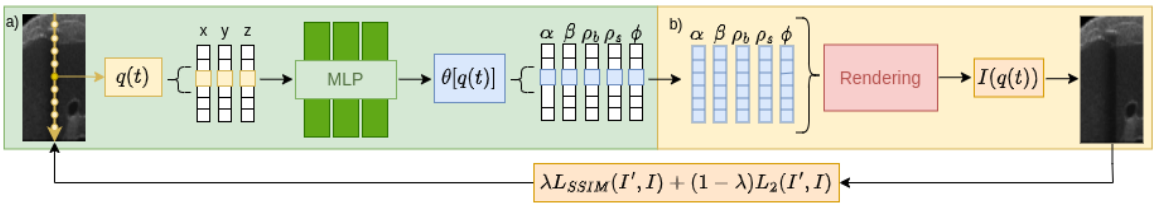

Figure 2: a) For a query point $q \in \mathbb{R}^3$ sampled along a ray, the MLP extracts a parameter vector $\theta \in \mathbb{R}^5$ from an implicit volume representation, b) from parameters at queried and preceding positions along the ray the rendering computes a per-query intensity. Resulting intensities compose an US image. The output and target frame are compared using a weighted sum of Structural Similarity Index Measure (SSIM) (Wang et al., 2004) and Squared Error Loss (L2).

3.1. Background: US Physics

US images are generated by mapping reflected sounds from the tissue within a thin transversal slice of the body. Intrinsic acoustic parameters such as travelling speed of sound, acoustic impedance, attenuation coefficient, and spatial distribution of sound scattering micro-structures are the main contributing factors affecting the sound reflection within the tissue. By knowing the mapping of these parameters in space, one would be able to simulate renderings of 3D US in arbitrary views (Salehi et al., 2015).

3.2. Ultrasound NeRF

Figure 2 presents our framework in the single-frame case. The method follows the original NeRF w.r.t its two components: a neural network (Figure 2a) and volumetric rendering (Figure 2b). The network represents a volume as a 3D vector-valued continuous function that maps a position $q = (x, y, z)$ in a Cartesian coordinate space into a parameter vector $\theta \in \mathbb{R}^5$ which elements correspond to attenuation α, reflectance β, border probability ρ_b, scattering density ρ_s, and scattering intensity ϕ and compose a final pixel intensity as outlined in Section 3.3. The parameter vector consists of isotropic physical tissue properties hence we do not provide explicit viewing directions to the network. This ensures that the regressed physical properties remain consistent between views, whereas the view-dependent changes are enforced by the rendering. Figure 1 illustrates definition of a ray and query points. We encourage the reader to refer to Appendix A for the network details.

3.3. Ultrasound Volume Rendering

Our US volume rendering model builds upon a formulation presented by Salehi et al. (2015) that proposes a ray-tracing-based simulation model. The advantage of this model is its flexibility in representing US artifacts coming from backscattering effects. For each scan-line r, Equation 3 defines a recorded US echo $E(r, t)$, measured at distance t from the transducer, as a sum of reflected $R(r, t)$ and backscattered $B(r, t)$ energy:

$$E(r, t) = R(r, d) + B(r, t) \tag{3}$$

The reflected energy is defined by:

$$R(r, t) = |I(r, t) \cdot \beta(r, t)| \cdot PSF(r) \otimes G(r', t') \tag{4}$$

Where the term $I(r, t)$ is the remaining energy at the distance t, $\beta(r, t)$ represents the reflection coefficient, and $PSF(r)$ is a predefined 2D point-spread function. G(r, t) admits 1 for points at the boundary and 0 otherwise. We compute it by sampling from a Bernoulli distribution parameterized by the border probability ρ_b. A probabilistic approach to the border definition reflects network's uncertainty about interaction of the ray with a tissue border. The energy loss is traced along each scan-line, and the remaining energy $I(r, t)$ is modelled using the loss of the energy due to reflection β at the boundaries and attenuation compensated by applying an unknown time-gain compensation (TGC) function. The final formulation for $I(r, t)$ assumes an initial unit intensity $I_0(r, 0)$ and loss of energy at each step dt. We can further simplify the resulting equation by modeling the compensated attenuation α by a single parameter since TGC is a scaling factor:

$$I(r, t) = I_0 \cdot \prod_{n=0}^{t-1} [(1 - \beta(r, n)) \cdot G(r, n)] \cdot \exp^{(-\int_{n=0}^{t-1} (\alpha \cdot f \cdot dt))} \tag{5}$$

Consequently, $\alpha's$ correspond to the physical attenuation only up to an unknown scaling factor. The backscattered energy $B(r, t)$ from the scattering medium is a function of remaining energy $I(r, t)$ and a 2D map of scattering points $T(r, t)$:

$$B(r, t) = I(r, t) \cdot PSF(r) \otimes T(r', t') \tag{6}$$

The map $T(r,t)$ is learnt using a generative model inspired by (Zhang et al., 2020):

$$T(r,t) = H(r,t) \cdot \phi(r,t) \tag{7}$$

In this model, $H(r,t)$ admits 1 for a query point being a scattering point and 0 otherwise. This function is sampled from the Bernoulli distribution parameterized by scattering density ρ_s. It represents the uncertainty of whether the scattering effect of a scattering point is observed. The intensity of a scattering point is controlled by its amplitude ϕ which models sampling from a normal distribution with the mean ϕ and unit variance.

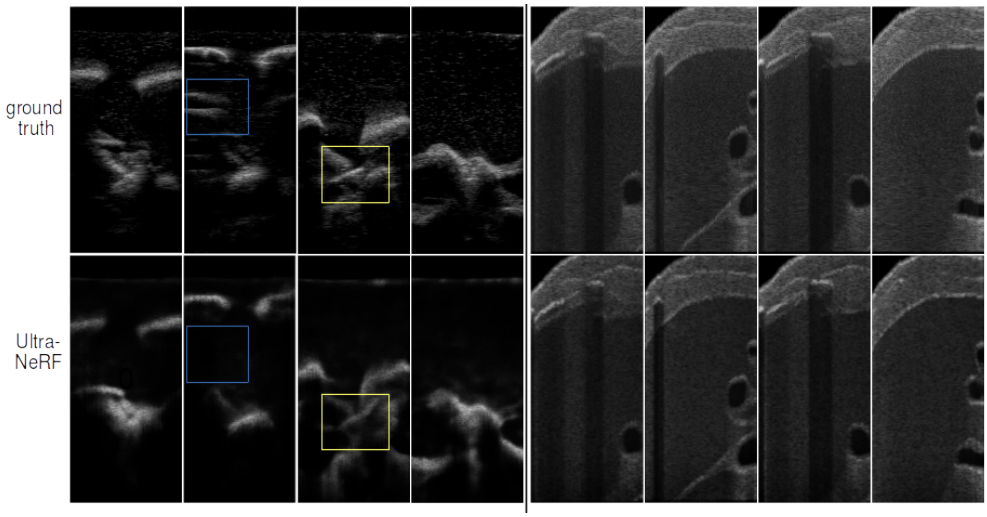

Figure 3: Our method infers novel views in phantom and synthetic data (bottom row). However, it does not produce artifacts inconsistent with our ray-based model, such as reverberations (blue), and it fails at representing complex structures (yellow).

Table 1: SSIM between synthetic and reference B-mode images.

dataset type		with rendering				w/o rendering			
		median	mean	min	max	median	mean	min	max
liver synthetic	tilted	0.47	0.45	0.41	0.60	**0.50**	0.51	0.46	0.59
	perpendicular	0.49	0.49	0.44	0.57	**0.54**	0.54	0.47	0.62
spine phantom	tilted	**0.54**	0.51	0.36	0.60	0.50	0.48	0.36	0.59
	perpendicular	**0.58**	0.54	0.42	0.65	**0.58**	0.54	0.41	0.64

4. Experiments & Results

Data. We acquired two types of data: synthetic and phantom B-mode images. For both datasets sweeps were recorded with different, constant perpendicular and tilt angles w.r.t

acquisition direction (Figure 1b). We tested our method on 6 sweeps covering views not present in the training set. We encourage the reader to refer to Appendix B for details about the datasets.

Quantitative Results. Table 1 presents evaluation of the quality of novel view synthesis as measured in terms of SSIM (Wang et al., 2004) between synthetic and reference testing data. To analyze the effect of rendering, we compared Ultra-NeRF to an implicit neural representation model without rendering. With rendering, we achieve better or similar results on our phantom data ($SSIM_{median} = 0.54$ for tilted and $SSIM_{median} = 0.58$ for perpendicular views), whereas the method without rendering attains higher SSIM values on our synthetic dataset ($SSIM_{median} = 0.50$ - tilted, $SSIM_{median} = 0.54$ - perpendicular).

Qualitative Results. Figure 3 illustrates examples of synthetic B-mode images generated with Ultra-NeRF while Figure 4 demonstrates the significance of rendering. We evaluated the quality of novel views by comparing volumes compounded from generated US images using Ultra-NeRF with and without the rendering function. We compounded volumes using compounding algorithm of the ImFusion [2].

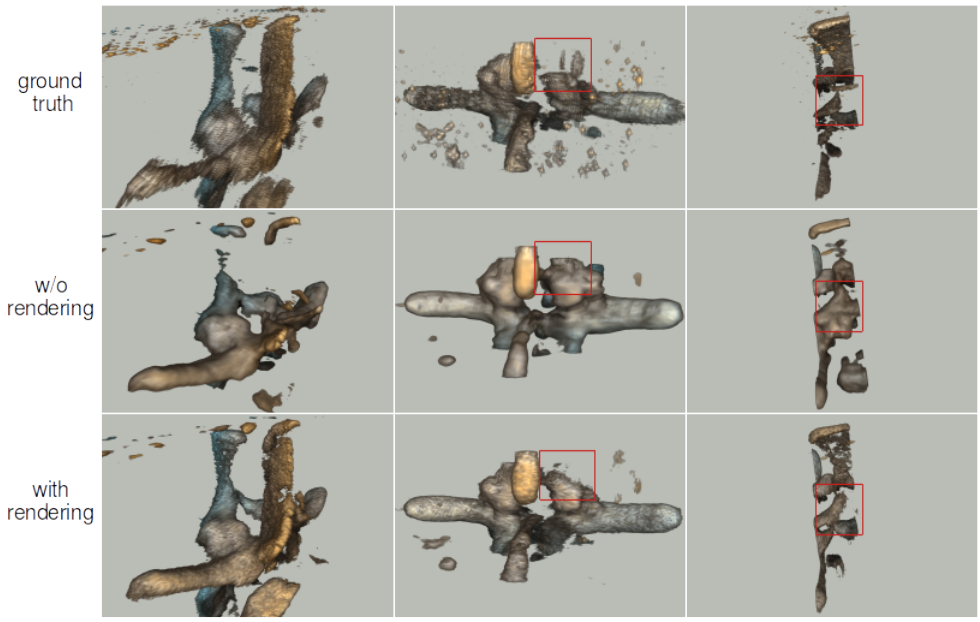

Figure 4: Compounded volumes: without rendering (middle row) the model is not aware of the viewing direction hence occluded parts of the lamina are reconstructed (red). By adding the rendering function, we introduce view-direction dependency needed to reconstruct anisotropic phenomena.

2. ImFusion GmbH, Munich, Germany, software version 2.42

5. Discussion & Conclusion

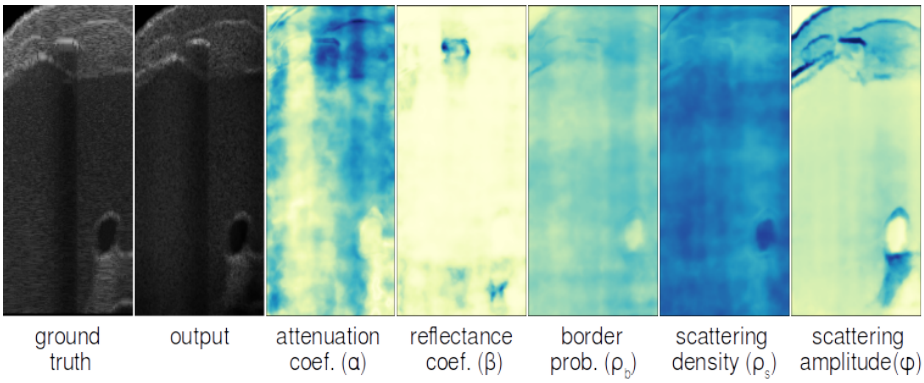

Figure 5: Intermediate maps illustrating each element of rendering parameter vector θ corresponding to a tissue's physical property.

In this paper, we present Ultra-NeRF, a volumetric INR of 3D US from a set of 2D US images. Unlike prior methods, our approach considers the anisotropic characteristics of US and addresses US volumetric rendering in a way that follows the physics of US. The experiments corroborate that Ultra-NeRF incorporates information about the viewing direction into a volumetric INR, which allows for the view-dependent synthesis of US frames, resulting in high-quality B-mode images. Decomposition of a rendered B-mode in the parameter space shown in Figure 5 further illustrates that Ultra-NeRF identifies tissue characteristics leading to differences in observed intensities. For example, it correctly determines a strongly reflective structure (a rib) by regressing a region with a higher reflectance and therefore produces acoustic shadow.

We propose a physically sound rendering method, however, further progress towards more realistic B-mode rendering requires addressing ray interactions and the Fresnel Effect. As shown in Figure 3, although the method learns accurate geometry, it does not allow to render complex US artifacts, such as reverberations. Additionally, to improve rendering results, future work may involve using deep learning techniques to establish a point spread function that reflects the underlying backscattering pattern. Another potential area for future research is regularization; the decomposition into parameter space is under-constrained, thus the outcome highly depends on the initial network configuration.

To the best our knowledge, this is the first work that explores the potential of implicit neural representations for medical US by addressing a rendering method specially designed for US. Therefore, it supports progress towards integrating the implicit 3D US representation exemplified with NeRF into medical applications. We believe that this work will inspire further exploration of implicit representations in US imaging for medical purpose.

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Appendix A. Network Structure

Our network is a fully-connected network, known as a multi-layer perceptron (MLP). It consists of 8 layers with 256 neurons. As discussed by Mildenhall et al. (2022), we are using positional encoding on an input vector, which maps it to a higher dimensional space to help the network learn high-frequency details. We are optimizing the weights of our network using the Adam optimizer (Kingma and Ba, 2014). Our loss is a weighted sum of SSIM and L2 between the rendered and true B-mode images and controlled by a parameter $\lambda \in [0, 1]$. In our experiments we used $\lambda = 0.9$.

Appendix B. Data

B.1. Synthetic data

We simulated B-mode images of a liver from CT images using ImFusion [3] Each sweep comprised 2D ultrasound images and respective tracking information. Our synthetic dataset consisted of seven sweeps: six with an acquisition angle tilted and one with an acquisition angle perpendicular w.r.t the acquisition direction (Figure 1b). Each sweep consisted of 200 2D US images with respective tracking information. The tilted sweeps differed in the slope's degree and direction. Therefore, an organ was observed from different viewing angles and directions. Our frames contained occlusions caused by scanning between ribs in different directions respective to the probe direction. We used four tilted sweeps for training, totalling 800 frames, and we tested on three sweeps: one perpendicular and two tilted, totalling 600 images.

B.2. Phantom data

We acquired phantom data of a lumbar spine, gelatine-based phantom. We used a robotic manipulator (KUKA LBR iiwa 7 R800) and linear probe to obtain ultrasound sweeps. The position of the probe was tracked using robotic tracking. We accessed real-time images and tracking information using ImFusion [3]. We scanned our phantom with a probe in paramedian sagittal orientation. The collected data comprised 13 sweeps with 150 frames each: six pairs of tilted sweeps and one perpendicular sweep. The trajectory of each pair

3. ImFusion GmbH, Munich, Germany, software version 2.42

of tilted sweeps was defined such that the data acquired for training completely covered tissue visible in the test data. To keep the constant spacing of images in each sweep and cover the whole testing region through training data, we reduced the number of testing frames per sweep to 100 frames. The scans occupied an area of two lumbar vertebrae. Analogously to synthetic data, the slope and direction of a probe differed between sweep pairs. As a consequence, the spinous process occluded different regions depending on the viewing direction (Figure 1). We used four tilted sweep pairs for training, totaling 1200 frames, and three sweeps for testing, totaling 300 images.