PHOCUS: Physics-Based Deconvolution for Ultrasound Image Enhancement

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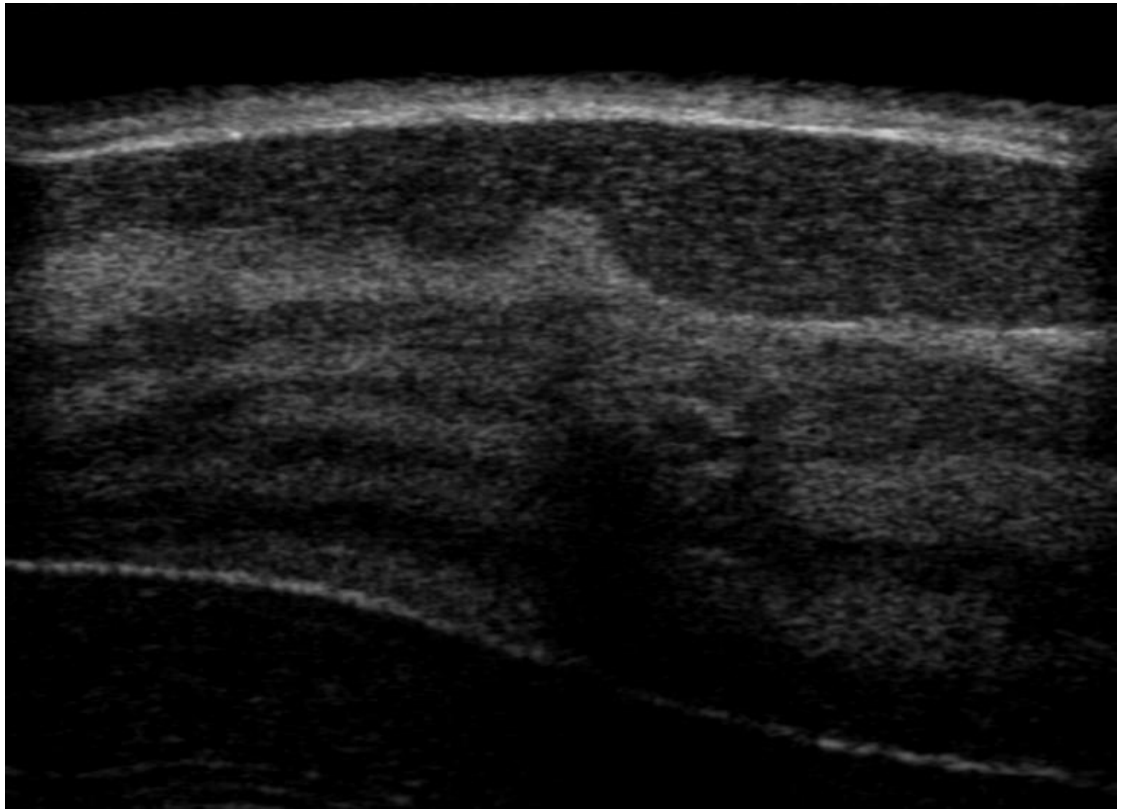
Motivation

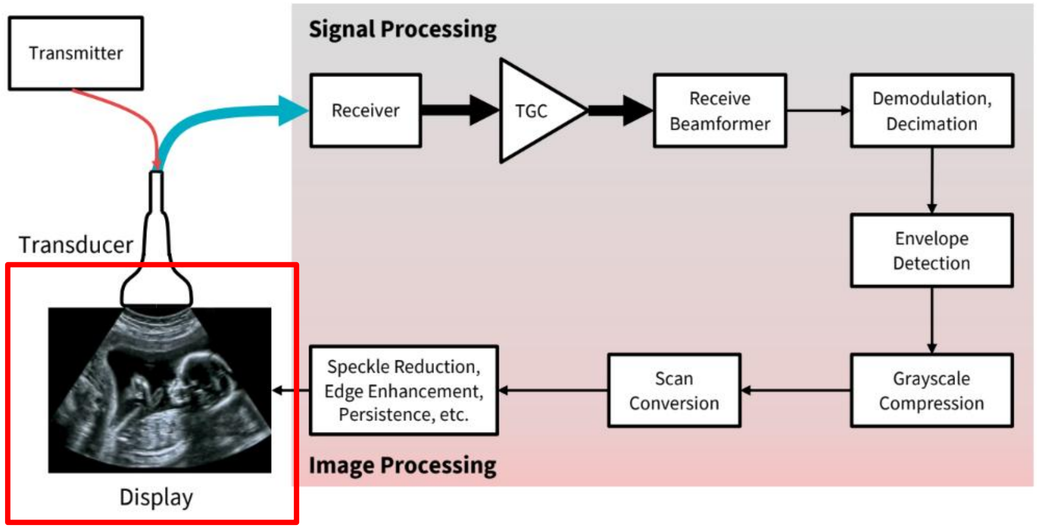
- Ultrasound Resolution is limited by e.g. diffraction and finite apertures that constrain diagnostic capabilities.
- Retrieving the exact location of reflectors and scatterers based on a processed B-mode image is difficult due to unknown acquisition parameters and processing steps

Resolution is limited in Ultrasound



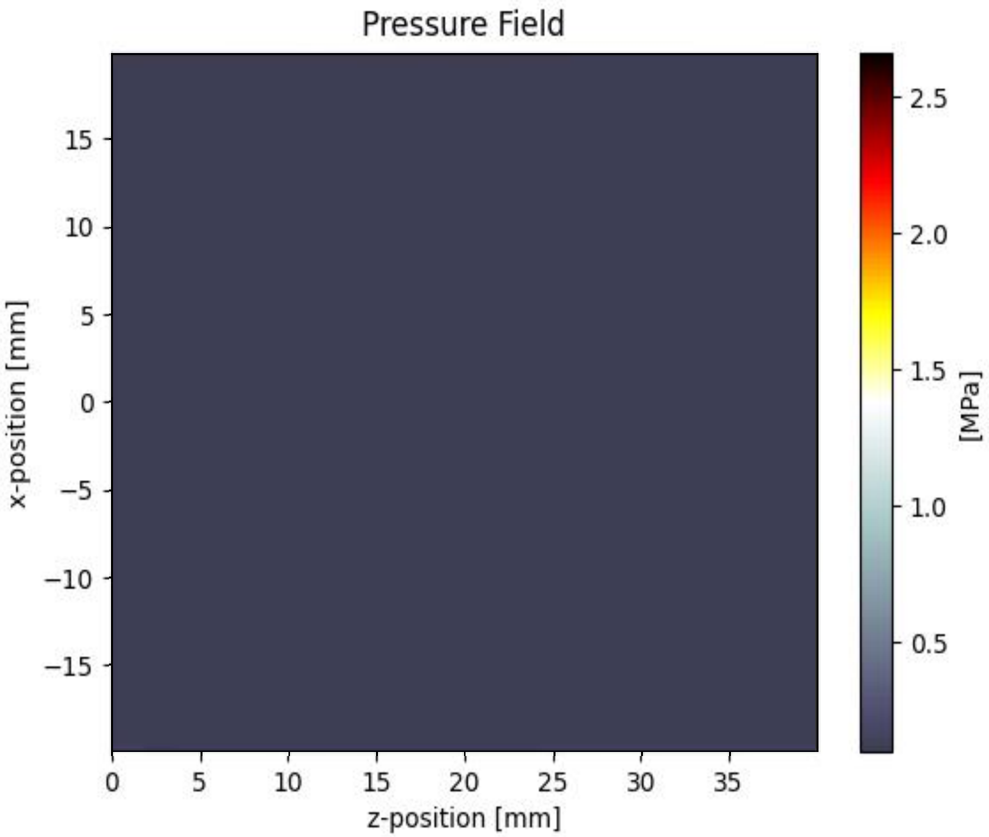
Motivation - Image Formation Process

Signal Processing Pipeline



[1]

Ultrasound Pressure Distribution



[2]

[1] Hyun, Dongwoon. "Advanced Ultrasound Imaging", Summer semester 2023, Stanford, University. Lecture.
[2] Created with k-wave-python: Yagubbbayli, F., Sinden, D., & Simson, k-Wave-Python, https://github.com/waltsims/k-wave-python .

Simplified Image Formation Process: Convolutional Model

The interaction between acoustic wave and tissue can be modeled by a convolution between a filter (defined by the imaging system) and the echogenicity map (defined by the interrogated tissue)

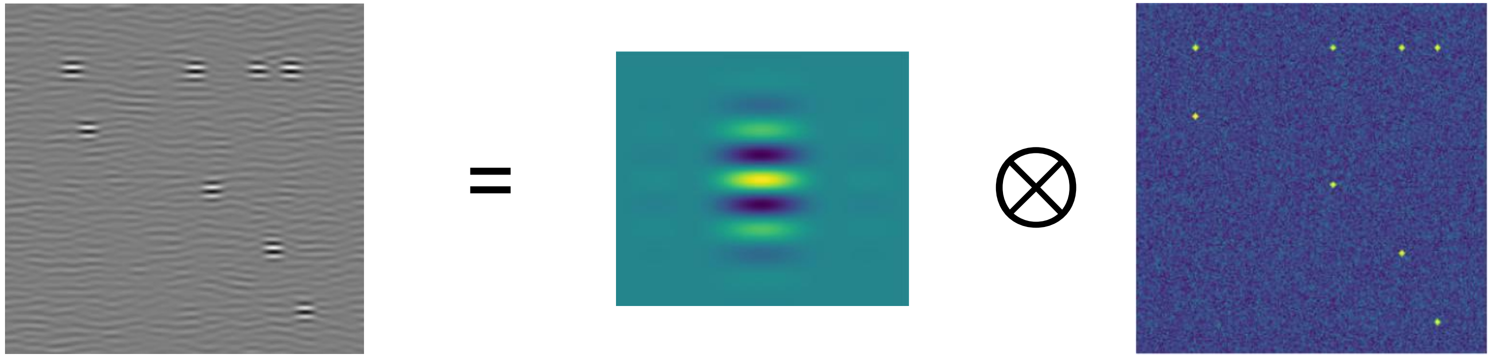
The convolutional model is a simplification of the image formation process based on the wave equations [1].

Filter:

- The filter is called the **Point Spread Function** (PSF) of the imaging system
- The PSF embodies acquisition parameters such as aperture size, acquisition frequency, etc.

$$y(z') = h(z') \otimes \gamma(z') + n(z')$$

y : radio-frequency data, h : PSF, γ = echogenicity map, n : gaussian noise, $\otimes$: convolution



 [1]: Jensen, J.A.: A model for the propagation and scattering of ultrasound in tissue, 89 (1), 182–190. https://doi.org/10.1121/1.400497

State-of-the-Art: Blind vs Non-Blind Deconvolution

Blind Deconvolution

- The PSF is found based on a data-driven approach [1]

Non-Blind Deconvolution

- Prior knowledge of the PSF is included and an analytical solution is acquired [2]

The derived PSF is used as the filter in deconvolution algorithms, such as the Wiener Filter, the Richardson-Lucy Algorithm, or in other optimization-based approaches like Maximum A Posteriori (MAP) estimation

→ But these methods **lack flexibility**, require careful **tuning of regularizers**, and necessitate **high computational resources** when applied to large datasets

[1]: Li, X., Zhang, X., Fan, C., Chen, Y., Zheng, J., Gao, J., & Shen, Y. (2024). Deconvolution based on sparsity and continuity improves the quality of ultrasound image. Computers in Biology and Medicine, 169, 107860.
[2]: Dalitz, C., Pohle-Frohlich, R., & Michalk, T. (2015). Point spread functions and deconvolution of ultrasonic images. IEEE transactions on ultrasonics, ferroelectrics, and frequency control, 62(3), 531-544.

Proposed Approach

- **Define a PSF** based on a set of known acquisition parameters and equations

- Learn a **continuous** representation of the echogenicity map based on the acquired B-mode images with an **Implicit Neural Representation** (INR)

  → At the core, a **memory efficient** and continuous multi-layer-perceptron (MLP) is updated based on mapping from a spatial location to a sensor output

- Instead of working on the RF-data directly we work on the more commonly **available B-Mode** imaging

  → To maintain the validity of the approach we use a **differentiable** signal processing pipeline starting from the convolutional model

PSF

We adapt the model from [1] for the definition of the PSF as the outer product of the lateral and axial pressure distribution:

$$h(x', z') = h_{lat}(x') * h_{ax}(z')$$

The **lateral pressure** distribution at the focal point can be written as a **convolution** of the Fourier transformation of the **transmit** A_T and **receive** function A_R :

$$h_{lat}(x' \mid \lambda, D, r) = \mathcal{F}(A_T) \otimes \mathcal{F}(A_R)$$

$$= D^2 \mathrm{sinc}^2\left(\frac{Dx'}{r\lambda}\right)$$

with D = Aperture and λ = wavelength.

Facilitating our pipeline, we remove the envelope detection step, in accordance with [2], and model the **axial signal** to:

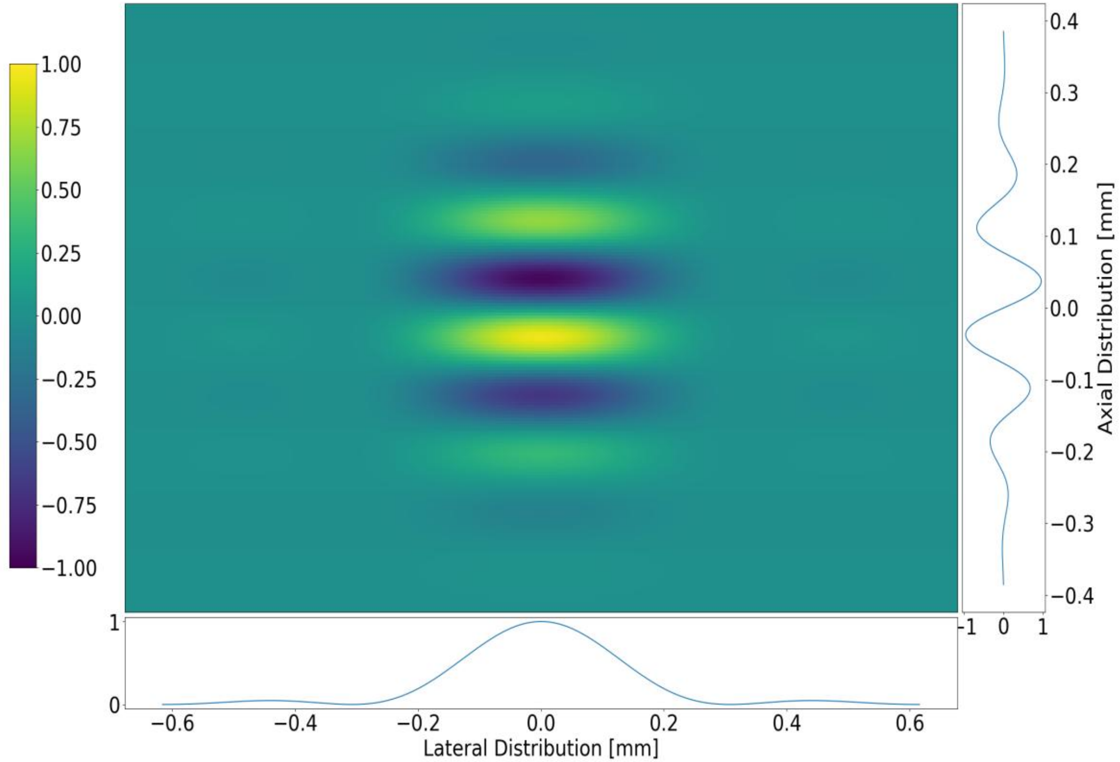
$$h_{ax}(z' \mid \sigma_z) = exp\left(-\frac{z'^2}{2 * \sigma_z^2}\right)$$

Where σ_z = scaling factor based on the number of cycles for the axial pulse.

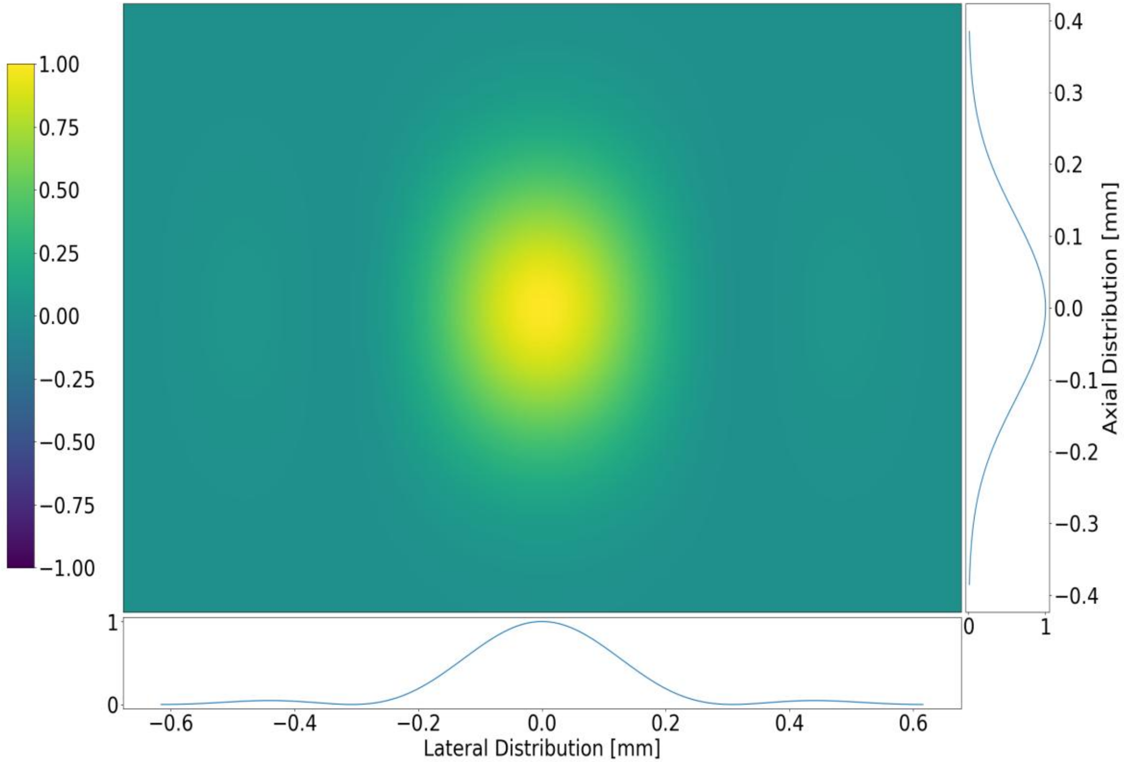
→ Assuming advanced beamforming algorithms such as aperture growth and synthetic aperture focusing we use a **spatially invariant PSF**

[1] Walker, W. F., & Trahey, G. E. (1998). The application of k-space in pulse echo ultrasound. IEEE transactions on ultrasonics, ferroelectrics, and frequency control, 45(3), 541-558.
[2] Dalitz, C., Pohle-Frohlich, R., Michalk, T.: Point spread functions and deconvolution of ultrasonic images. IEEE transactions on ultrasonics, ferroelectrics, and frequency control 62(3), 531–544 (2015)

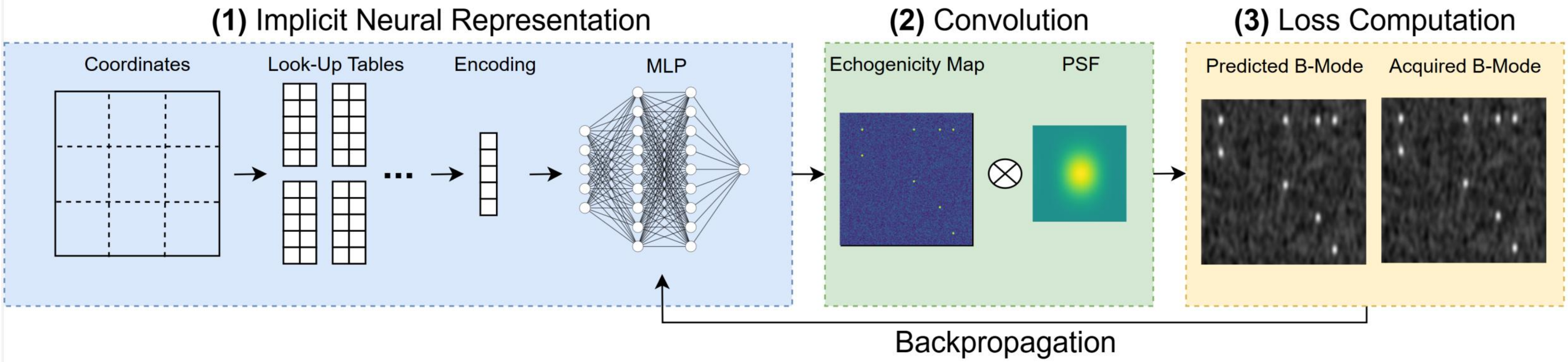
PSF



Envelope
Detection



Proposed Pipeline

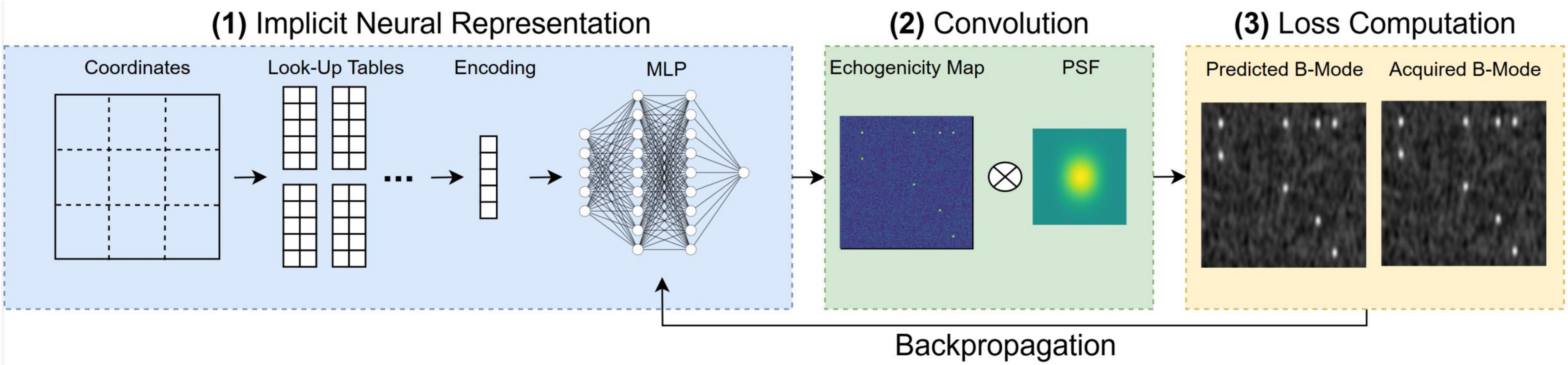


(1) Implicit Neural Representation [1]:

- For a given input coordinate x, the surrounding grid vertices are associated with an entry in a **look-up table**
- The look-up table contains a **learnable feature vector** per vertice, which is used as the input to a bilinear interpolation
- An **L-dimensional multi-resolution grid** provides L entries which are concatenated to form the input to the MLP
- The MLP outputs a single scalar value based on the encoded input

[1]: Müller, T., Evans, A., Schied, C., & Keller, A. (2022). Instant neural graphics primitives with a multiresolution hash encoding. ACM transactions on graphics (TOG), 41(4), 1-15.

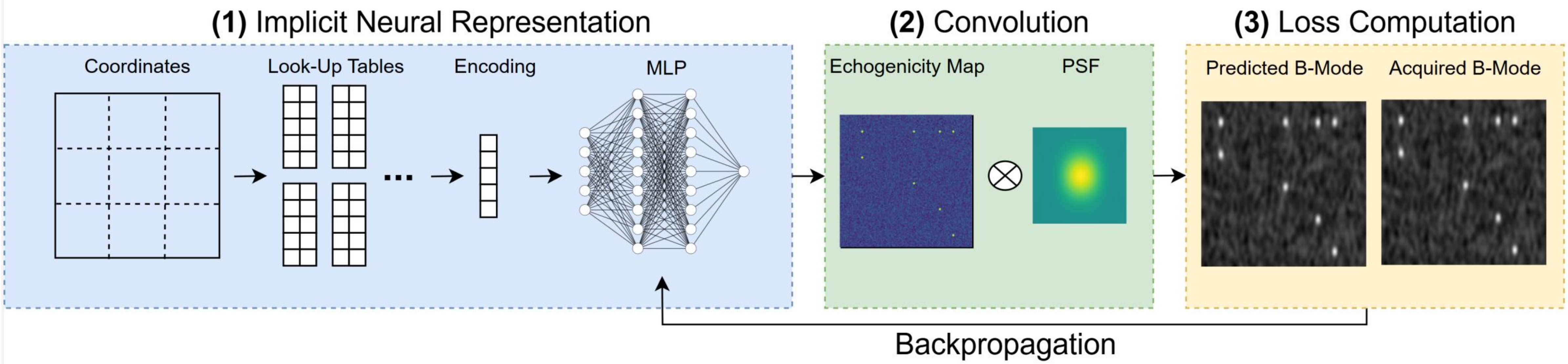
Proposed Pipeline



(2) Differentiable Image processing pipeline

- The output of the MLP provides the echogenicity map which is convolved with an isotropic PSF
- A differentiable signal processing pipeline transforms the convolved data via log-compression to the imaging domain

Proposed Pipeline



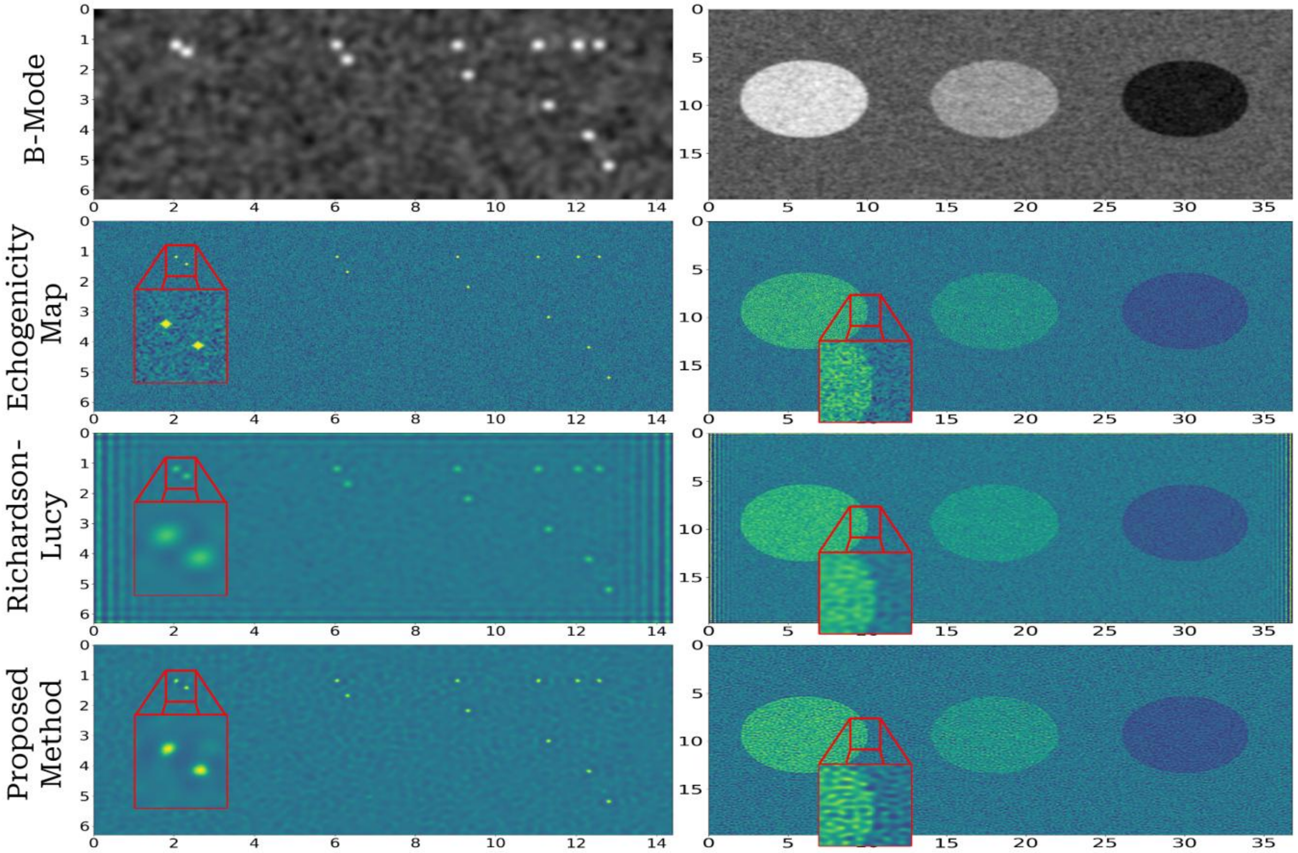
(3) Loss Computation

- Loss function: Combination of a total variation loss (TV), structural similarity index (SSIM) loss, and a mean-squared error (MSE) loss

Synthetic Results

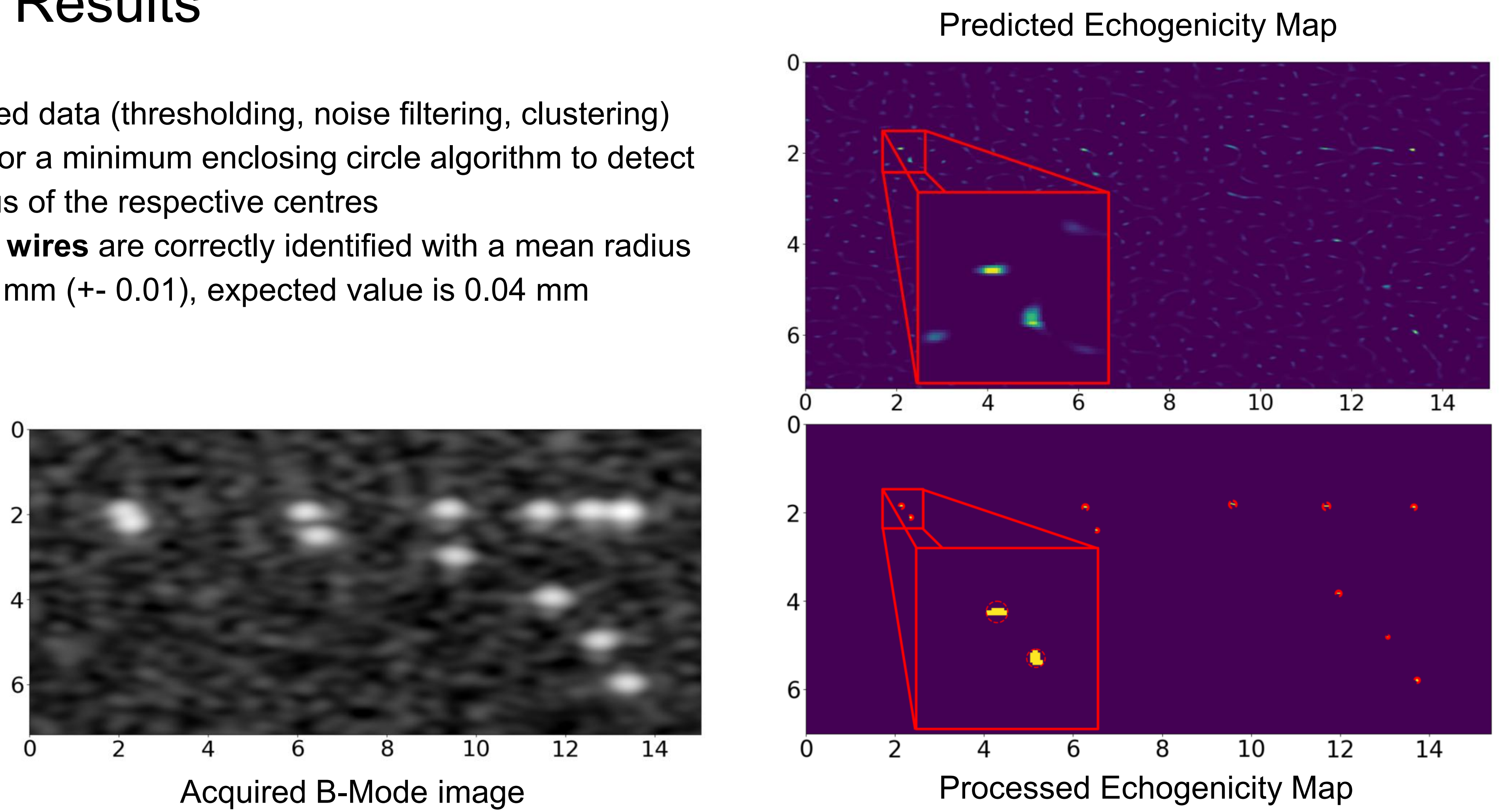
- Comparison with the Richardson-Lucy Algorithm
  - Iterative approach for deconvolution (takes the same PSF)
- Synthetic images are created with a PSF (f = 10 MHz, pulses= 5, f-number = 2.0)

	Cylindrical Inclusions		**Wire Targets**	
	PSNR	SSIM	PSNR	SSIM
Richardson-Lucy	16.89	0.21	17.35	0.06
Proposed Method	**17.85**	**0.29**	**17.85**	**0.07**



In-Silico Results

- Processed data (thresholding, noise filtering, clustering) is used for a minimum enclosing circle algorithm to detect the radius of the respective centres
- **10 of 12 wires** are correctly identified with a mean radius of 0.053 mm (+- 0.01), expected value is 0.04 mm



Summary

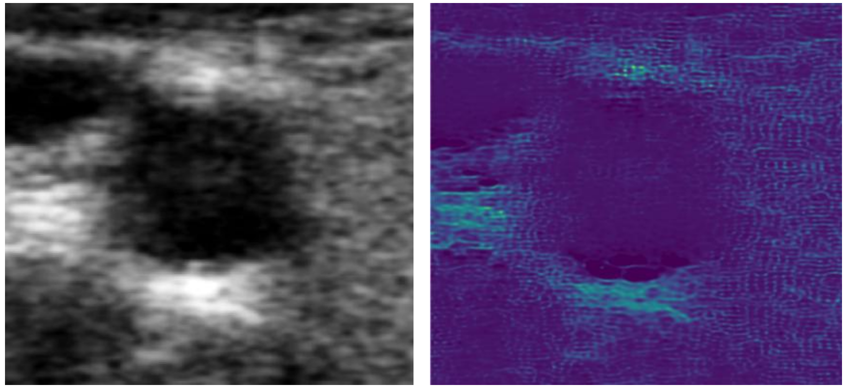
Contributions:

- We propose to leverage an **INR for learning a continuous representation** of the echogenicity map based only on the B-mode image and a deconvolutional model
- We developed a **fully differentiable rendering pipeline** which integrates a PSF that is based on known equations

Limitations:

- So far only works on 2D
- Due to the problem being ill-posed, it is necessary to empirically estimate some parameters (e.g. log-compression factor)
- Spatial invariance of the PSF limits the solution

→ We show that using an INR for the US deconvolution task **works successfully** and that it **enhances the resolution** of the US images



For more experiments and further discussion let us meet at the Poster

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Paper

Code

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