Compact Implicit Neural Representations for Plane Wave Images

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1/ Motivation and contribution

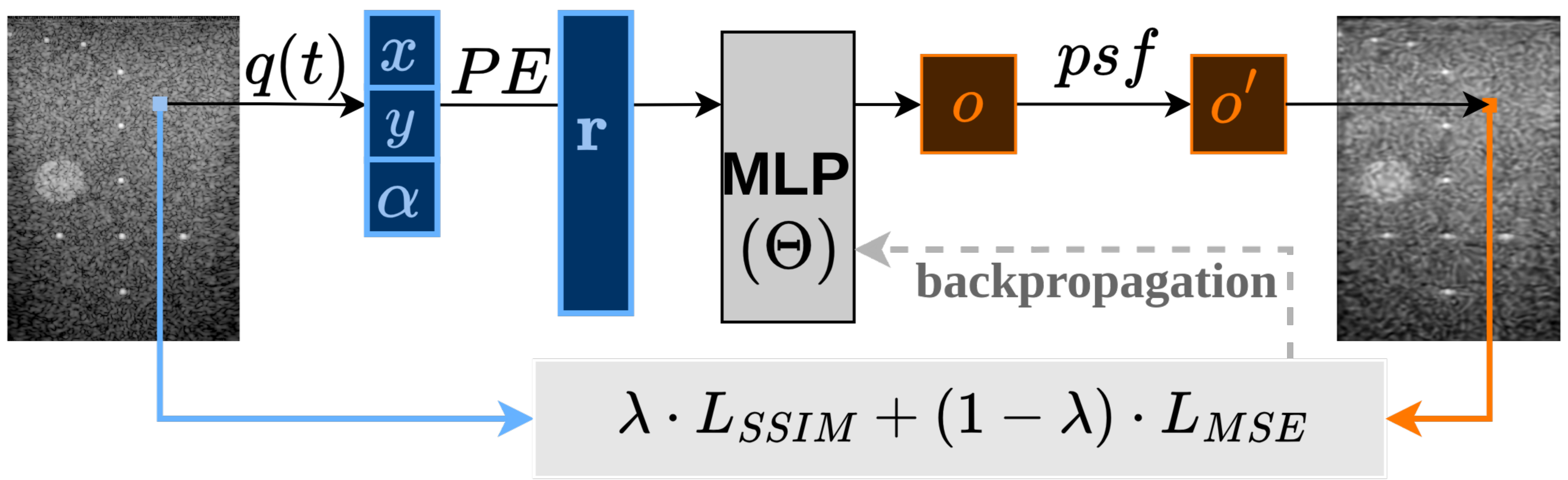
- Plane Wave (PW) imaging often produces artifacts and shadows that vary with insonification angles ;
- Implicit Neural Representations (INRs) have proven adept at accurately representing intricate 3D scenes and generating novel views [1] ;
- We propose a novel approach using INRs to compactly encode multi-planar sequences while preserving crucial orientation-dependent information.

2/ Represent PW images with an INR

The core of the proposed INR model is a coordinated-based neural network (NN). The input of the NN is the pixel position at a specific PW angle denoted as :

$$q(t) = [x, y, \alpha]^T, \tag{1}$$

where x and y refer to the lateral and axial coordinates, respectively, and α denotes the PW angle. A Positional Encoding (PE) is used to transform the input data $q(t)$ into a higher-dimensional embedding. The output of the model is the predicted intensity for $q(t)$; fhe final prediction o' is obtained by applying a point spread function (psf) on the intermediate prediction o.



The loss function, which measures the discrepancy between predicted intensities (o') and actual intensities (*Ground Truth (GT)*), integrates both the Structural SIMilarity (SSIM) and Mean Squared Error (MSE) metrics. It is defined as :

$$\lambda \cdot L_{SSIM}(o', GT) + (1 - \lambda) \cdot L_{MSE}(o', GT) \tag{2}$$

where λ is empirically set to 0.75.

3/ Representation ability according to train set size

The speed of ultrasound data acquisition depends on the Pulse-Repetition Frequency (PRF). Reducing the number of required PW angles shortens the acquisition time. To identify the minimum number of angular views necessary for training an effective INR capable of synthesizing unseen angles, we assess the model's sensitivity to the number of training angles.

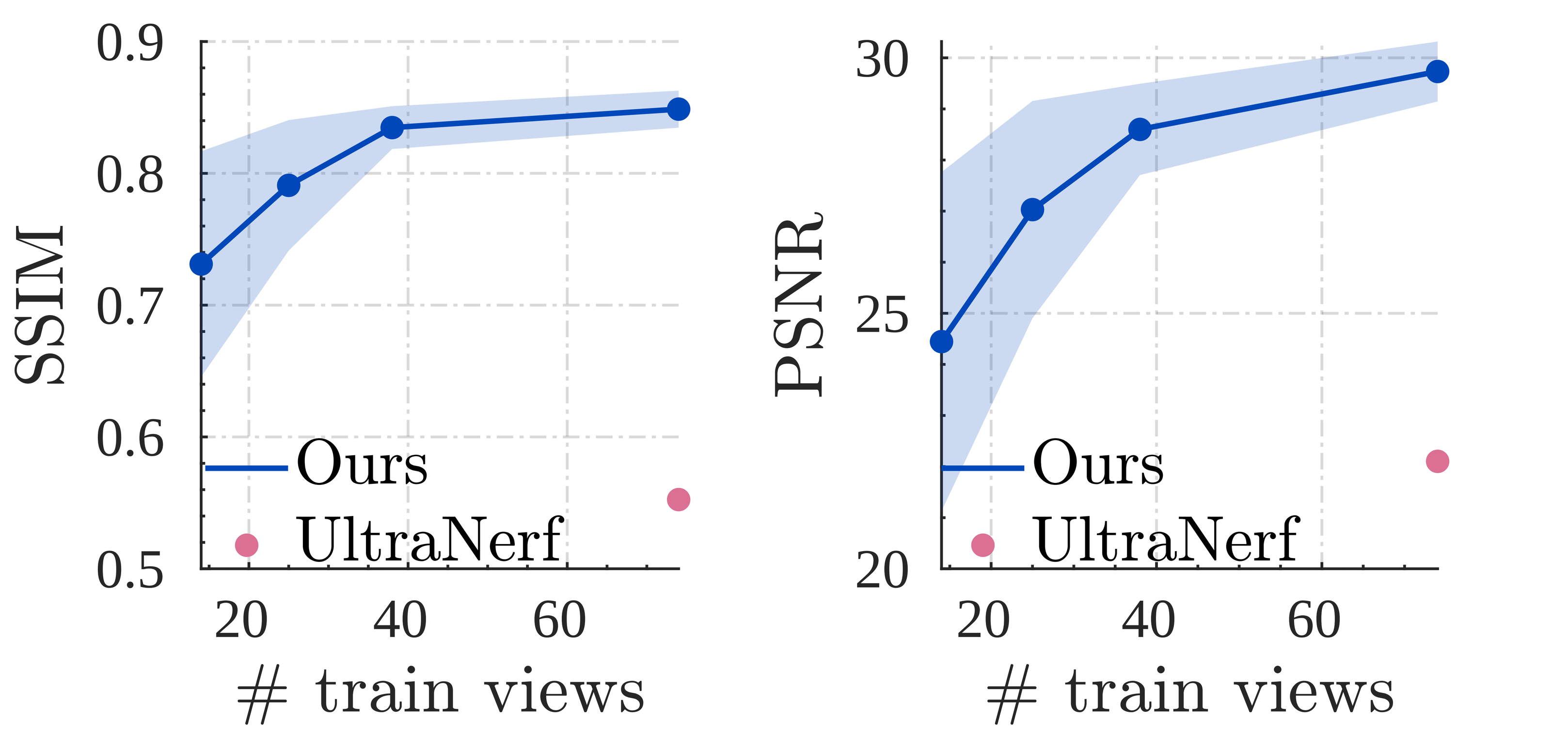


Figure 1 – Quantitative comparison of image quality conservation capability on the *SR* dataset. 30000 iterations, calculated between GT and o'

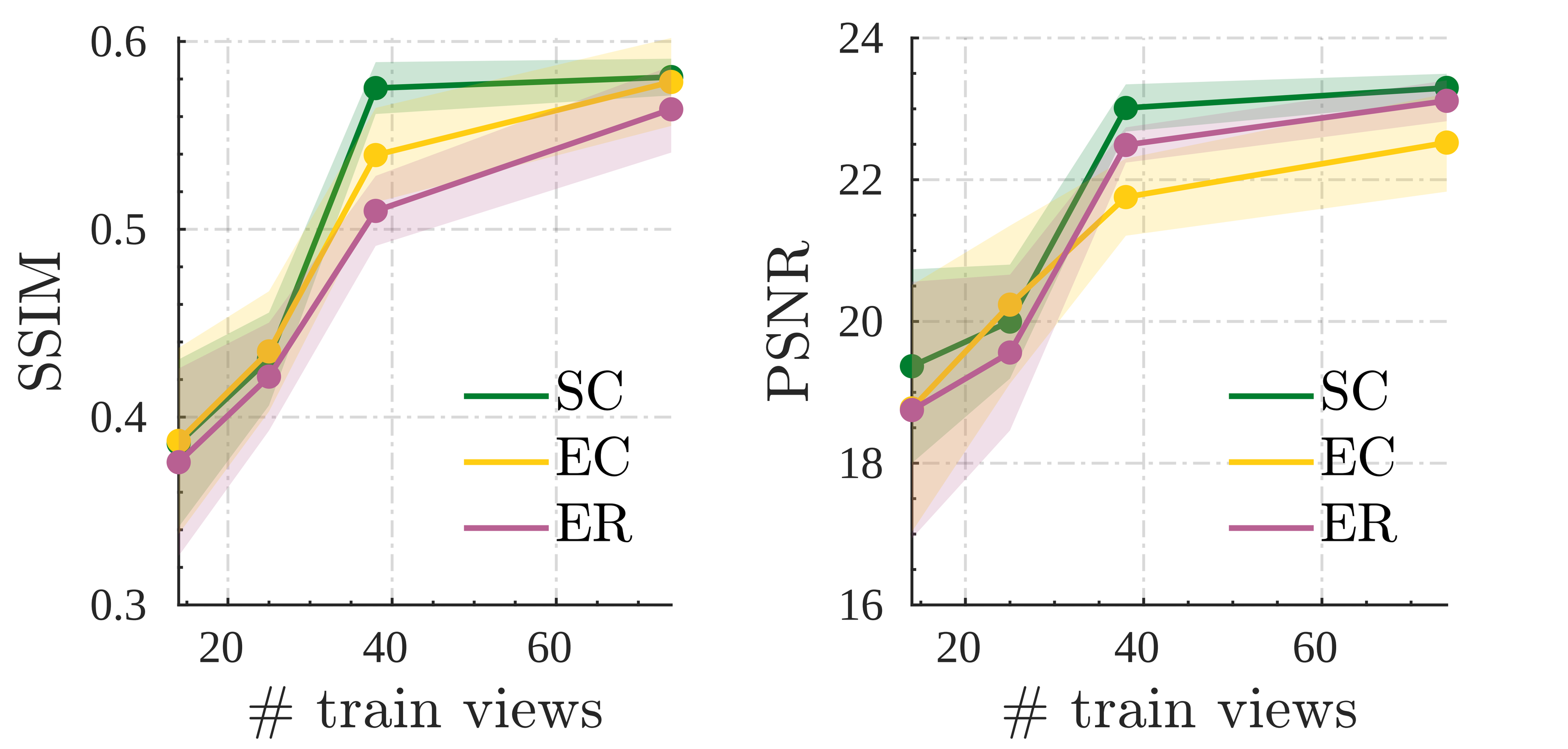


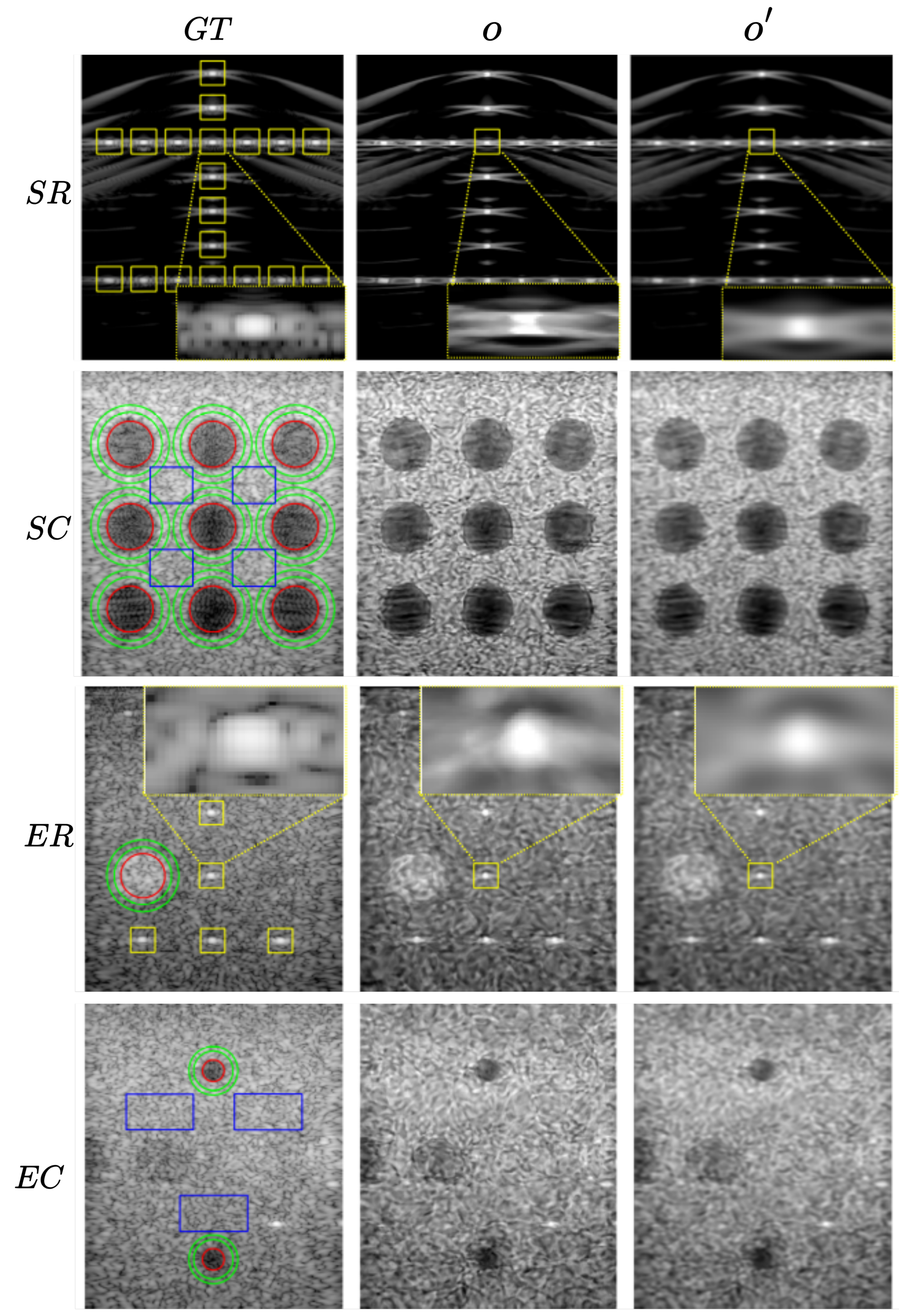
Figure 2 – Quantitative comparison of image quality conservation capability on the *SC*, *ER*, *EC* datasets. 10000 iterations, calculated between GT and o'

4/ Impact of the rendering method

The results demonstrate the effectiveness of the proposed model in generating images from unseen PW views. The model was trained on 38 views.

Table 1 – Quantitative comparison. Best bolded, second best underlined.

		GT	o	o′
SR	FWHM_A [mm]↓	0.40	0.45	**0.39**
	FWHM_L [mm]↓	0.81	0.71	**0.63**
SC	CNR [dB]↑	8.08	7.77	**10.04**
	SNR↑	7.03	5.54	**8.42**
ER	FWHM_A [mm]↓	0.55	**0.47**	0.50
	FWHM_L [mm]↓	0.89	**0.70**	0.76
	CNR [dB]↑	5.63	5.72	**7.39**
EC	CNR [dB]↑	7.74	9.17	**11.45**
	SNR↑	6.66	6.75	**8.80**



The intermediate predictions, generated before applying 2-D Gaussian blurring, produce images with sharp edges that improve spatial resolution but at the expense of reduced contrast and lower background SNR. In contrast, the final output (o') achieves a superior overall balance by combining the enhanced background SNR and contrast from the rendering process with the improved spatial resolution seen in the intermediate predictions.

5/ Conclusion

- **Storage efficiency** our model's weights, saved in a .npy file, occupy 530 KB, while storing 75 PW images requires 8 MB, resulting in a compression ratio of approximately 15 :1 ;
- **Efficacy** of this representation is quantitatively assessed using SSIM and PSNR across varying training sizes, and compared against a state-of-the-art method [2].

References

[1] B. Mildenhall, P. P. Srinivasan, M. Tancik, J. T. Barron, R. Ramamoorthi, and R. Ng, "Nerf : Representing scenes as neural radiance fields for view synthesis," *Communications of the ACM*, vol. 65, no. 1, pp. 99–106, 2021.

[2] M. Wysocki, M. F. Azampour, C. Eilers, B. Busam, M. Salehi, and N. Navab, "Ultra-nerf : Neural radiance fields for ultrasound imaging," in *Medical Imaging with Deep Learning (MIDL)*, 2024.