Enhancing Acoustic Neural Predictors with Heterogeneous Density

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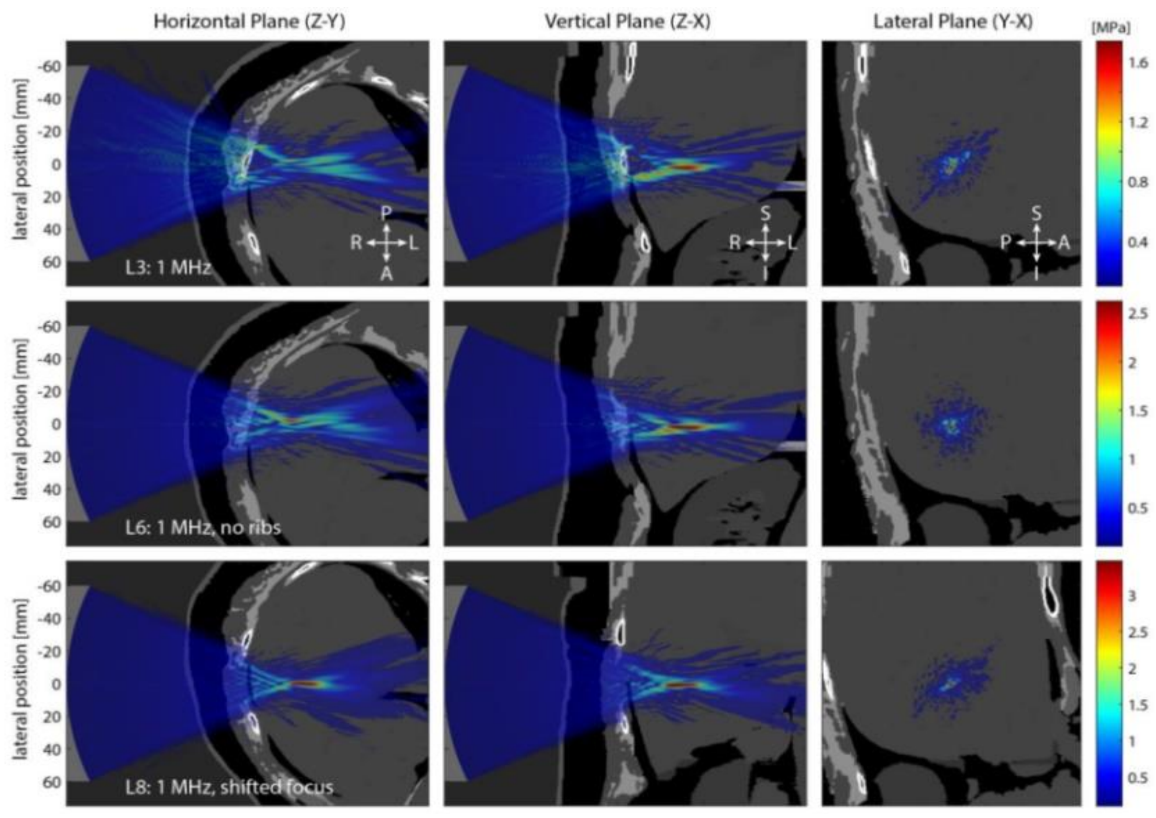
1 Introduction

The search for the optimal treatment plan in a focused ultrasound-based procedure is a complex multi-modal problem. It aims to deliver a solution within a clinically relevant time frame while maintaining precision above a critical threshold. We must balance clinical speed with precision. Machine learning offers a promising solution, as a recent neural predictor for acoustic skull propagation speeds up simulations significantly. In this work, we propose enhancing the predictive capabilities of this neural predictor by incorporating heterogeneous density information. By integrating data on varying densities within the skull structure, we aim to further improve the accuracy and robustness of the predictor, thus facilitating more precise treatment planning in focused ultrasound procedures.



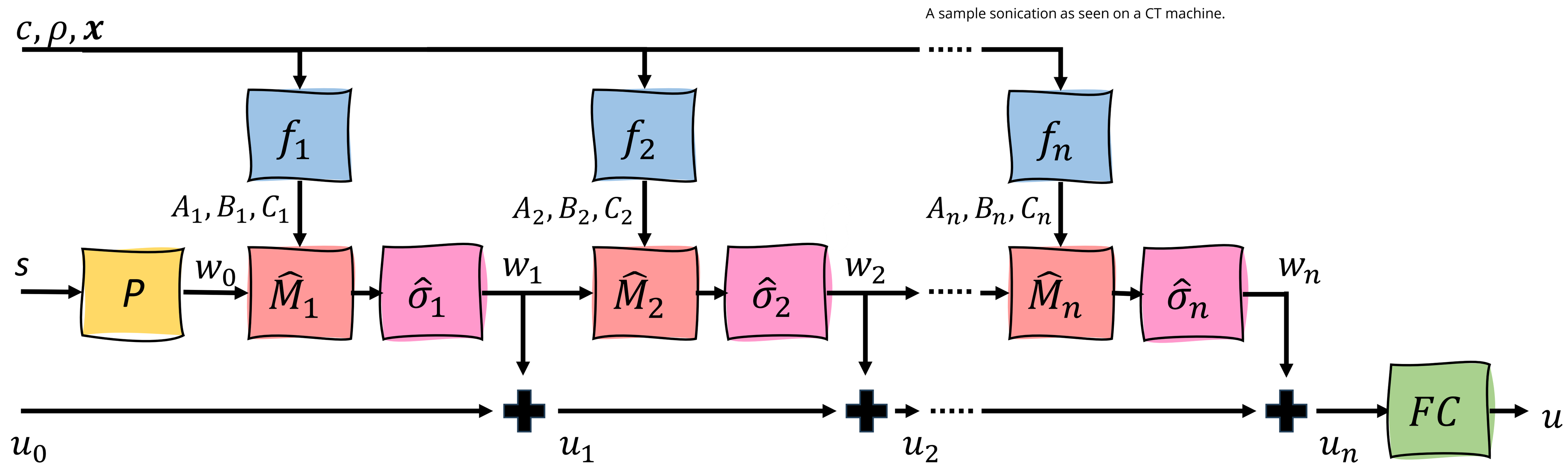
A sample sonication as seen on a CT machine.

1 Learned Born Series Enhanced With Density

- Architecture and implementation follows Convergent Born Series
- Created to overcome the bad convergence rate of the CBS when using strongly scattering media
- Finding generalised preconditioner and modified Green's operator
- Based on Fourrier Neural Operator

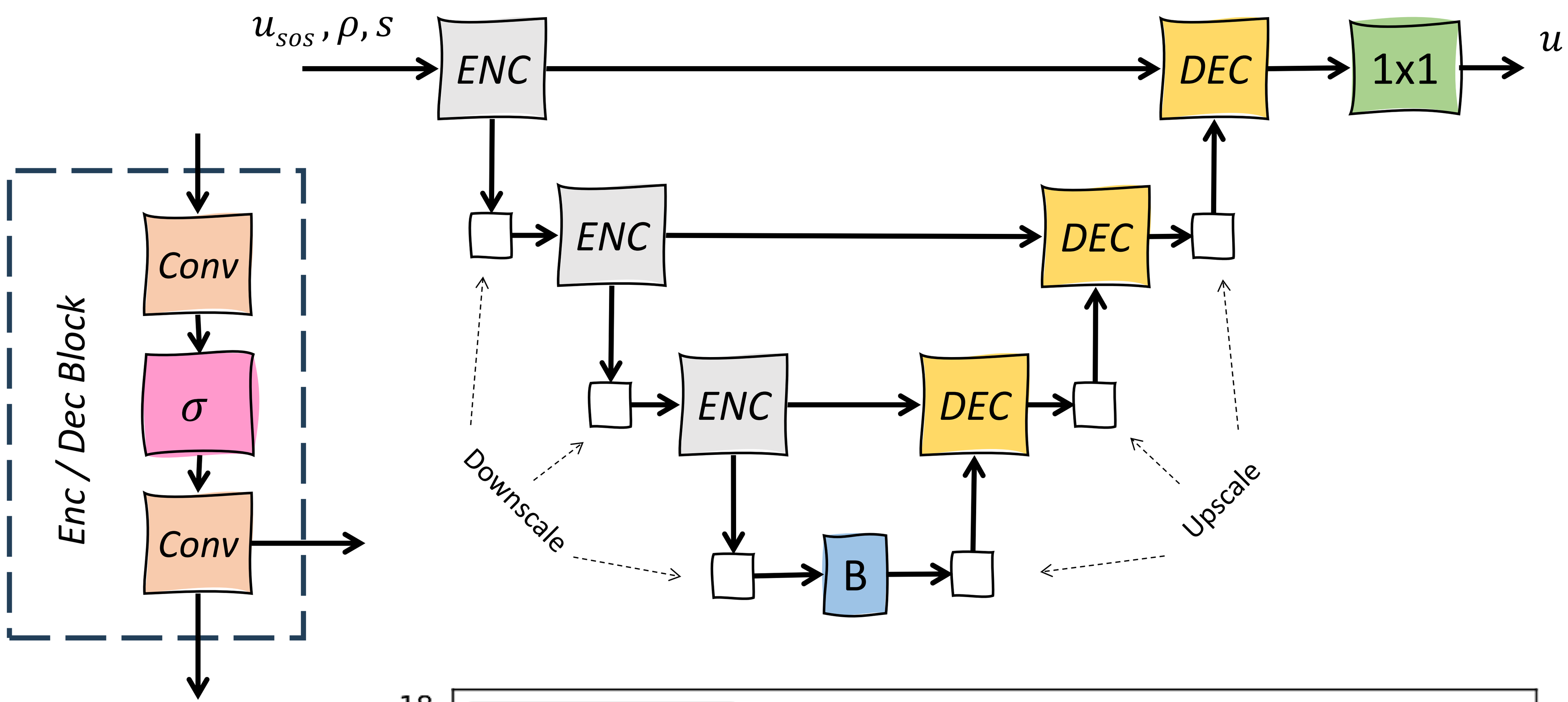
$$\hat{\mathcal{G}}_\theta = \mathcal{F}^{-1}(\alpha p^2 - \kappa^2 - i)^{-1}\mathcal{F},$$

$$\hat{\mathcal{M}}_\theta = (A_\theta \hat{\mathcal{G}}_\theta B_\theta + C_\theta).$$



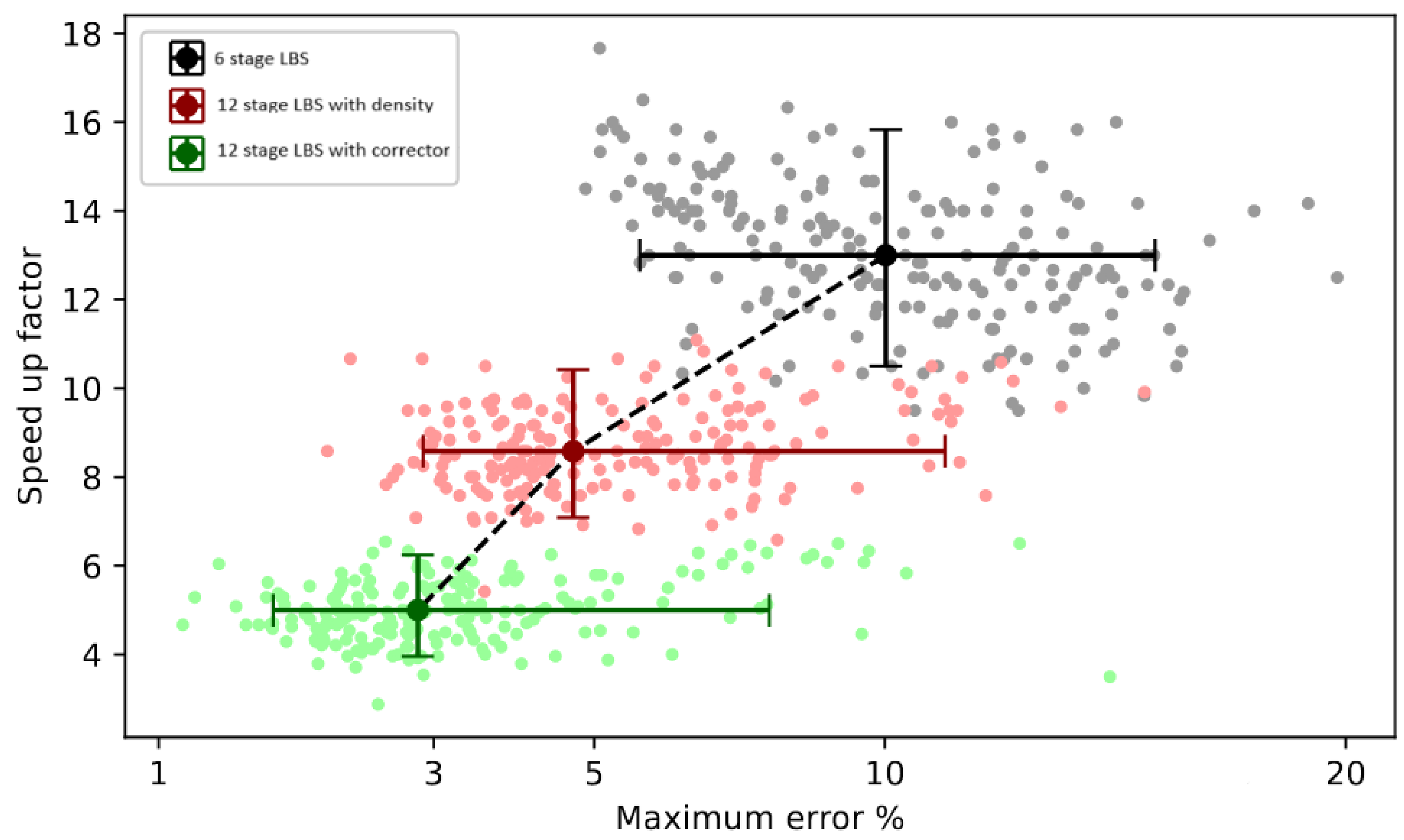
2 Corrector UNet

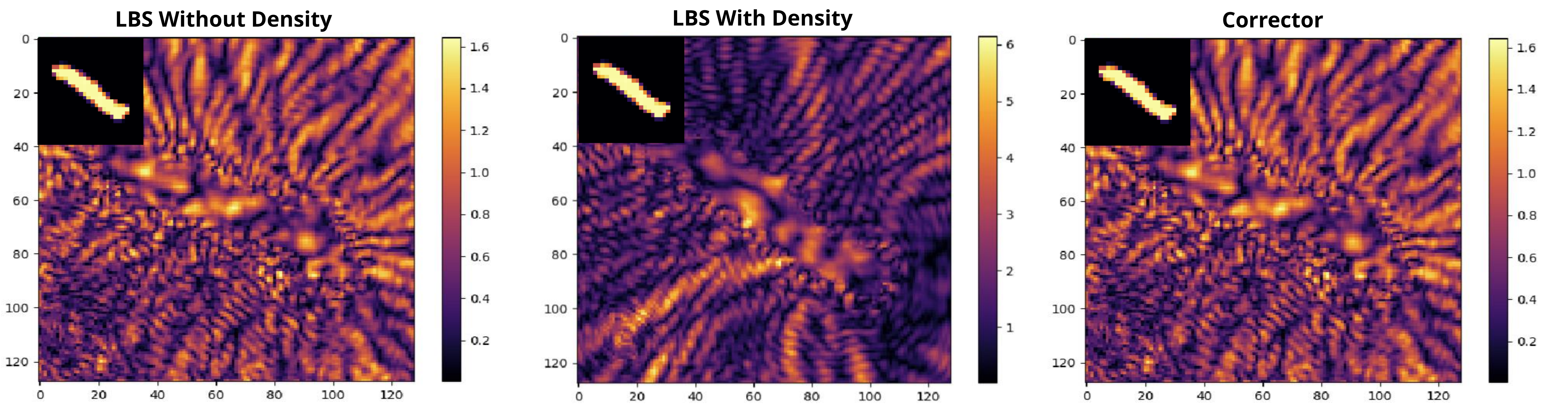
- Universal corrector model, invariant to what generates the input pressure
- Fast and small transformer architecture
- Transforms pressure fields generated purely from speed of sound map into density corrected ones
- Using known double conv block for each encoding and decoding block
- Downscale implemented as an avgpool operation, upscale is a transposed convolution filter



3 Results

- 4000 MNIST images, rescaled to 128x128 and used as sound speed and density distributions
- Tissue contrast the same as brain / skull contrast
- Ground truth data generated using the Helmholtz solver in j-Wave using GMRES with a fixed source position
- All networks were trained with a batch-size of 16 and learning rate of $3 \cdot 10^{-3}$
- Dataset split 80:10:10
- Gelu activation, AdamW optimizer, training on 8 x A100 and capped at 8 hours
- Corrector is using 12 stage LBS without density to generate SoS fields for correction





Relative percentage differences between generated solution and a simulated one

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