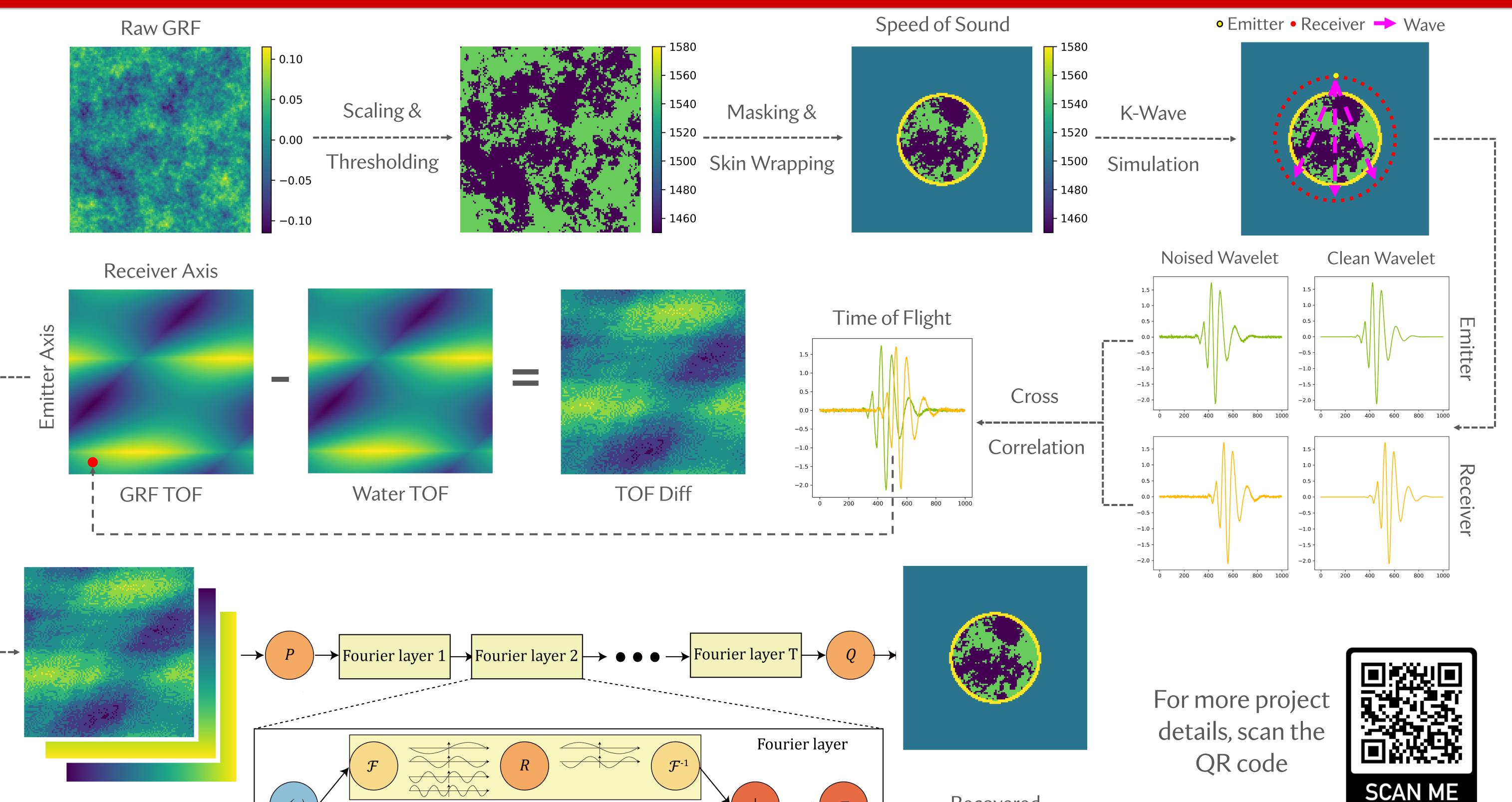
Neural Operator Learning for Ultrasound Tomography Inversion



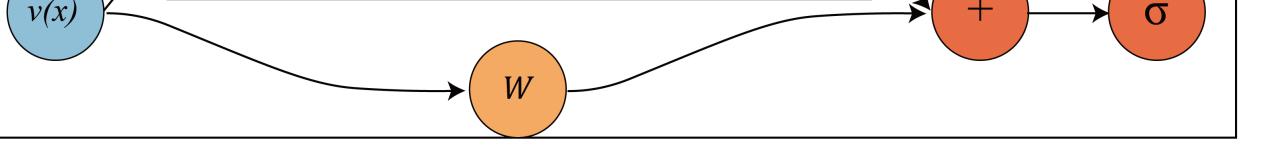
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Concatenate TOF Diff w/ Positional Encoding



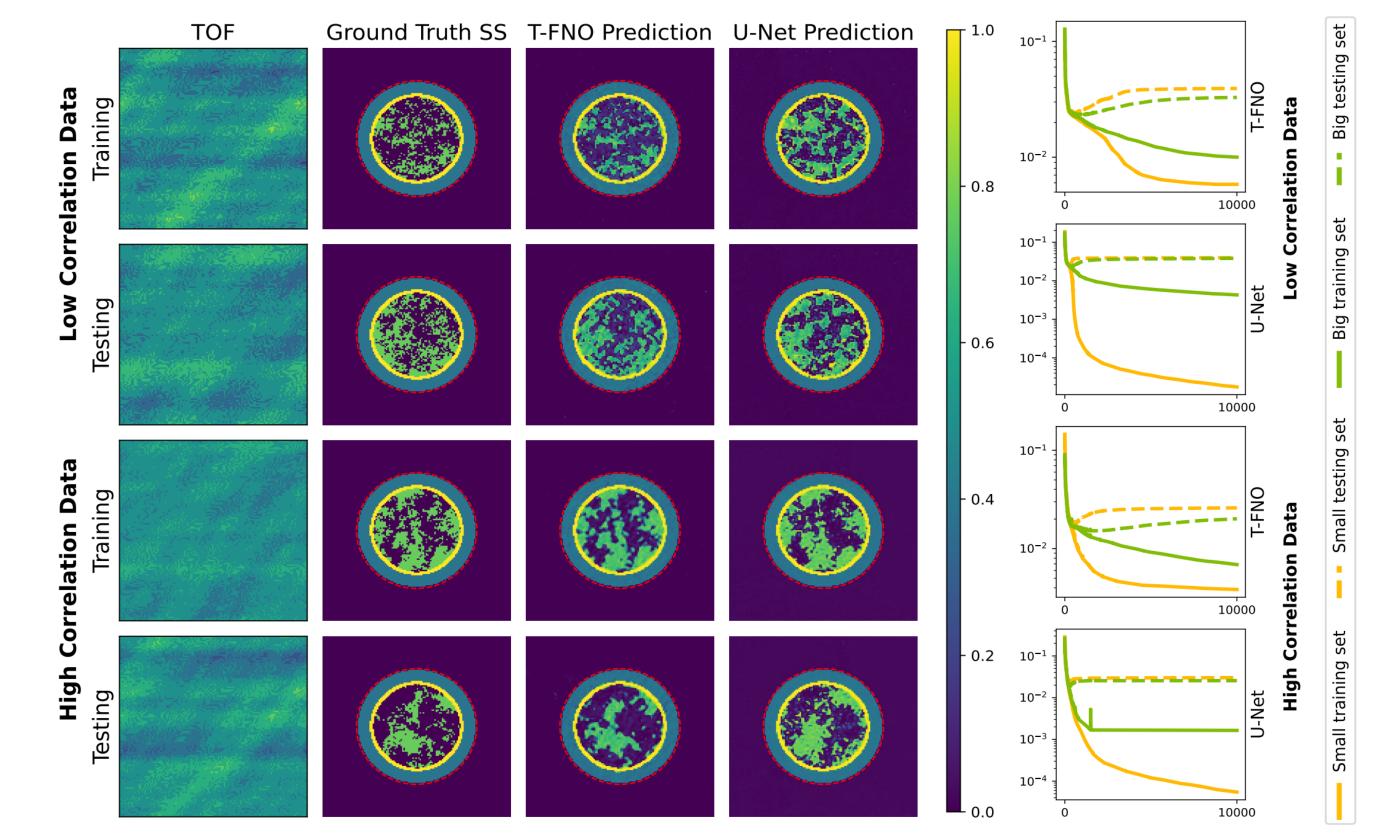
Recovered Speed of Sound

INTRODUCTION

Ultrasound computed tomography (USCT) is an emerging image modality for estimating the acoustics properties of an object using the transmission of sound waves. Due to its low cost and radiation free property, USCT has received significant attention. However, conventional full wave inversion (FWI) is computationally expensive and memory burdensome, thus hampering the widespread application of FWI to USCT breast imaging. We proposed to leverage neural operator [1] to solve the time-of-flight (TOF) USCT problem, namely learning the mapping between TOF data and the heterogeneous speed of sound (SOS) field.

METHODOLOGY

- 1. Generating Gaussian random fields (GRFs) as SOS field to emulate the variations in soft tissue;
- 2. Using k-wave MATLAB toolbox [2] to run a full-wave numerical forward simulation over the heterogeneous SOS fields and a homogeneous density fields, given an equally distributed set of 128 emitter locations and



generalization error, even when additional examples were provided.

CONCLUSION

Our novel problem formulation and application of the T-FNO improves over the baseline U-Net, laying the foundation for real-time accurate predictions of soft tissue distribution for tumor identification on breast imaging.

128 receivers on a ring (locate on red dashed line);

- 3. Calculating the TOF discrepancy by cross correlating the emitter and receiver signals and subtract it with the TOF of water-only SOS;
- 4. Concatenating the TOF discrepancy with positional encoding;
- 5. Training a tensorized Fourier neural operator (T-FNO, 64 modes, 32 hidden channels, and 32 projection channels) with the tensor in step 4 as input and corresponding SOS field as output;
- 6. Inferencing new sample with the trained T-FNO.

RESULTS

We observe that the T-FNO outperforms the U-Net at test time under all conditions, whereas the U-Net better fits the training set but does not generalize well. T-FNO better captures the overall trends in the data, while the U-Net is prone to overfit the training data. This is also shown in the loss convergence plots, in which the U-Net suffers from considerable

REFERENCES

[1] Z. Li, et. al. Fourier neural operator for parametric partial differential equations. arXiv preprint arXiv:2010.08895, 2020.
[2] BE Treeby et. al. k-wave: Matlab toolbox for the simulation and reconstruction of photoacoustic wave fields. Journal of Biomedical Optics 15, 2010.

ACKNOWLEDGEMENT

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