Deep Unfolding of Full Waveform Inversion for Quantitative Ultrasound Imaging

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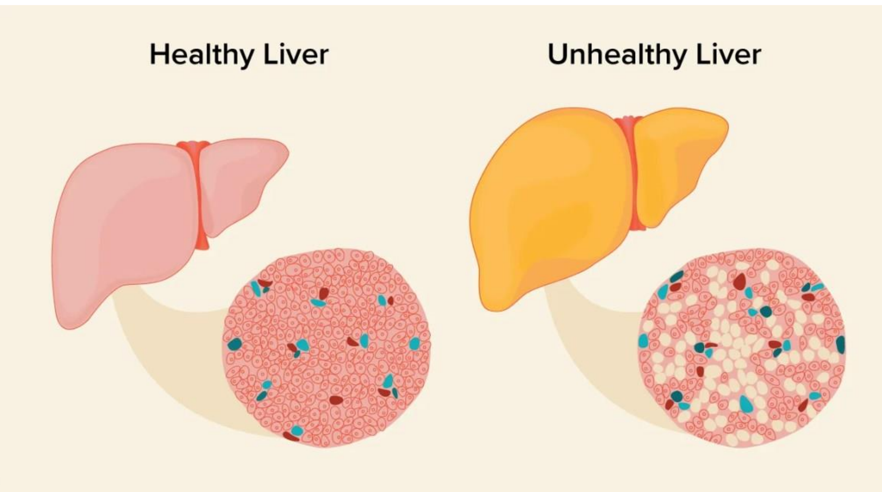
⋆ Equal Contribution

The paper

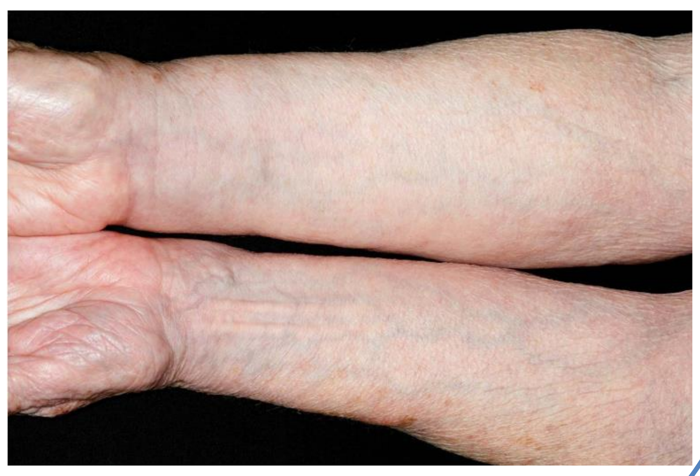
Our Lab

1. Motivation and Contributions

- **Need for Quantitative Ultrasound:** Traditional ultrasound imaging does not reconstruct physical properties like the speed of sound, which are crucial for medical applications.
- **Limitations of FWI:** provides quantitative imaging but is computationally expensive and prone to local minima.
- **Deep Unfolding Potential:** Recent deep unfolding methods show promise in improving efficiency but are limited in detail recovery.
- **DUFWI:** A novel deep unfolding-based approach for faster and more accurate quantitative ultrasound imaging.
- **Efficient Training Strategy:** Uses block-wise training to reduce computational complexity while maintaining high reconstruction quality.
- Superior Performance: Outperforms classical FWI and previous deep unfolding methods, especially in noisy and out-of-distribution scenarios.

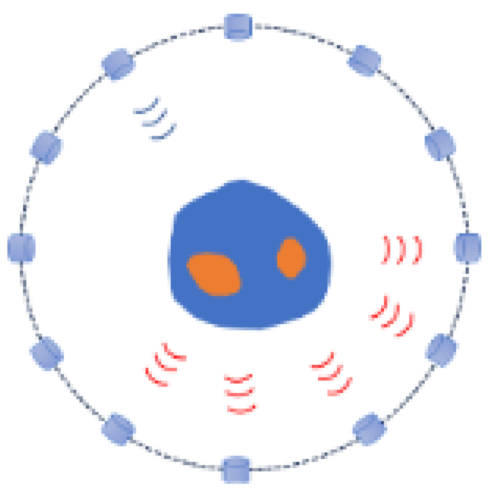


Fatty liver



Edema

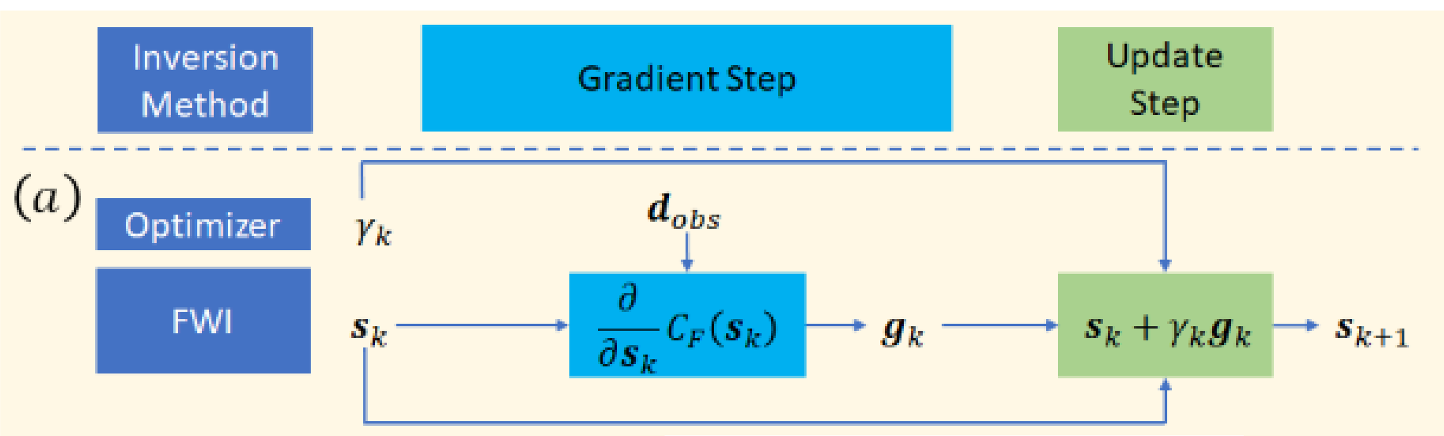
2. Forward model and Inverse Methods



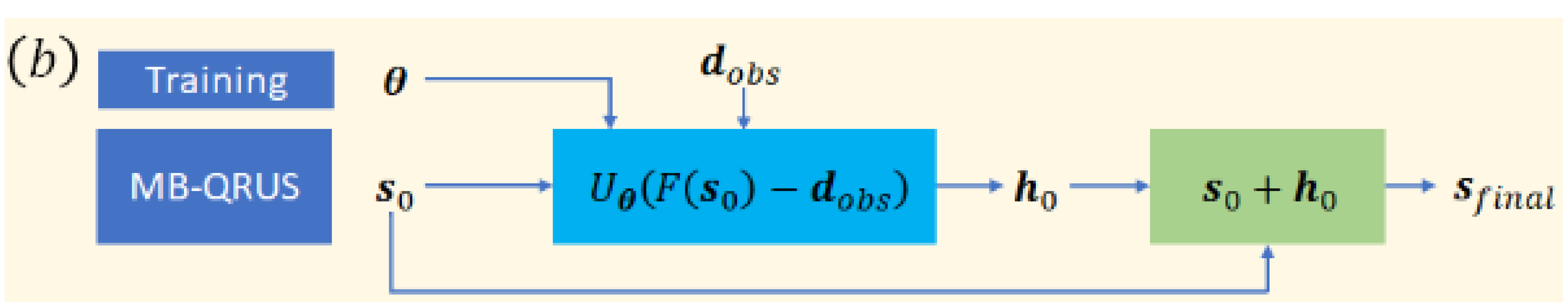
$$\mathbf{d} = F(\mathbf{s}),$$

FWI $$C_F(\mathbf{s}) = \|\mathbf{d}_{\text{obs}} - F(\mathbf{s})\|_2^2.$$

$$\mathbf{s}_{k+1} = \mathbf{s}_k + \gamma_k \mathbf{g}_k, \quad \mathbf{g}_k = \frac{\partial}{\partial \mathbf{s}_k} C_F(\mathbf{s}_k),$$



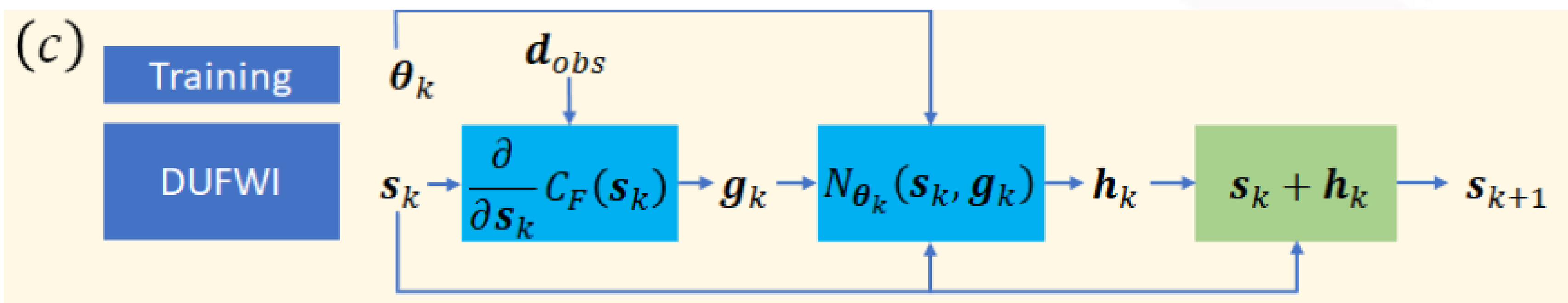
MB-QRUS $$\mathbf{s}_{final} = \mathbf{s}_0 + \mathbf{h}_0,$$



4. DUFWI

- Deep unfolding takes an existing solver and turns it into a model-based network.
- We unfolded FWI by turning the gradient step into a learned network

$$\mathbf{s}_{k+1} = \mathbf{s}_k + \mathbf{h}_k$$



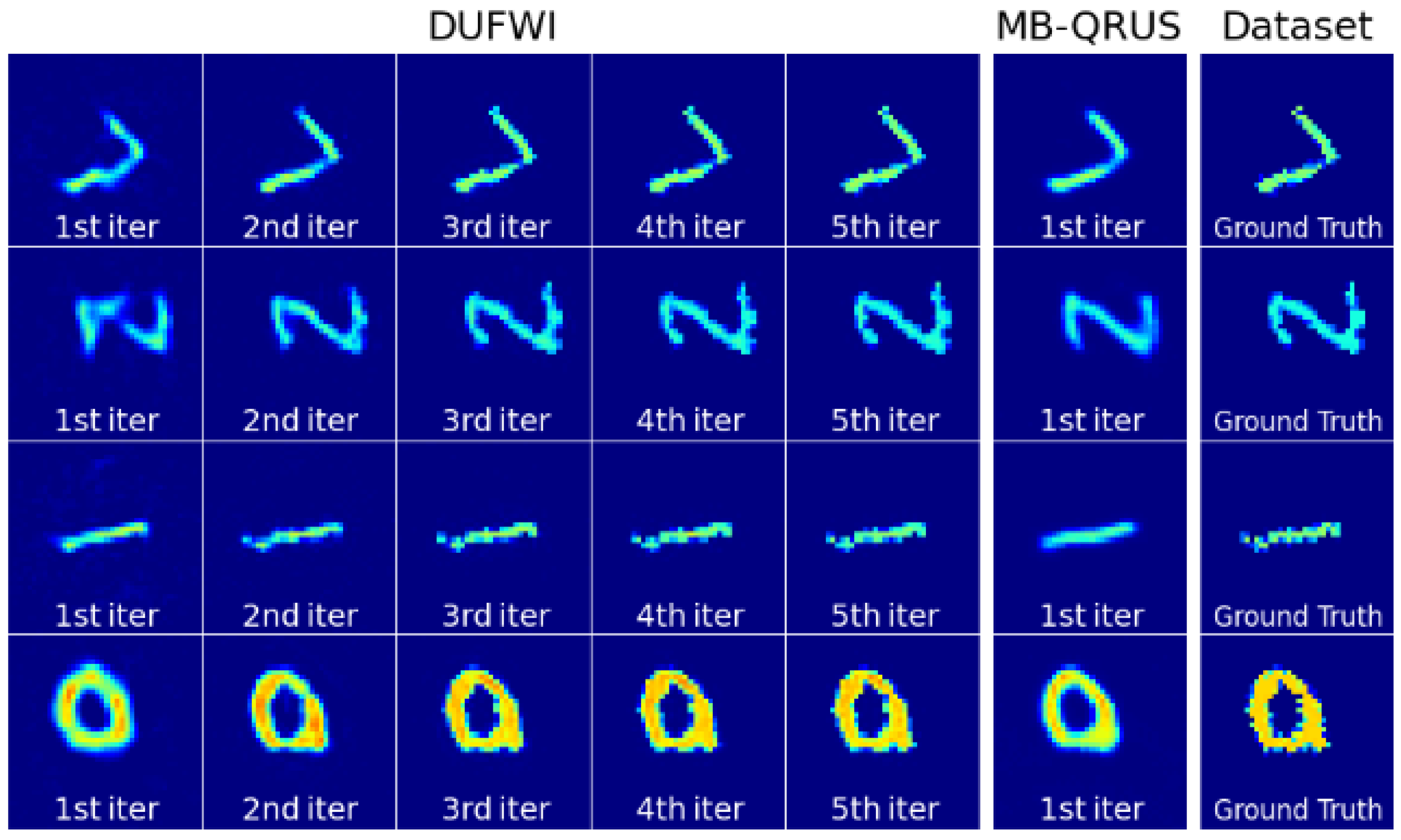
Sequential Training

Dataset $\{(\mathbf{d}_{\text{obs}}^{(i)}, \mathbf{s}_{gt}^{(i)})\}$

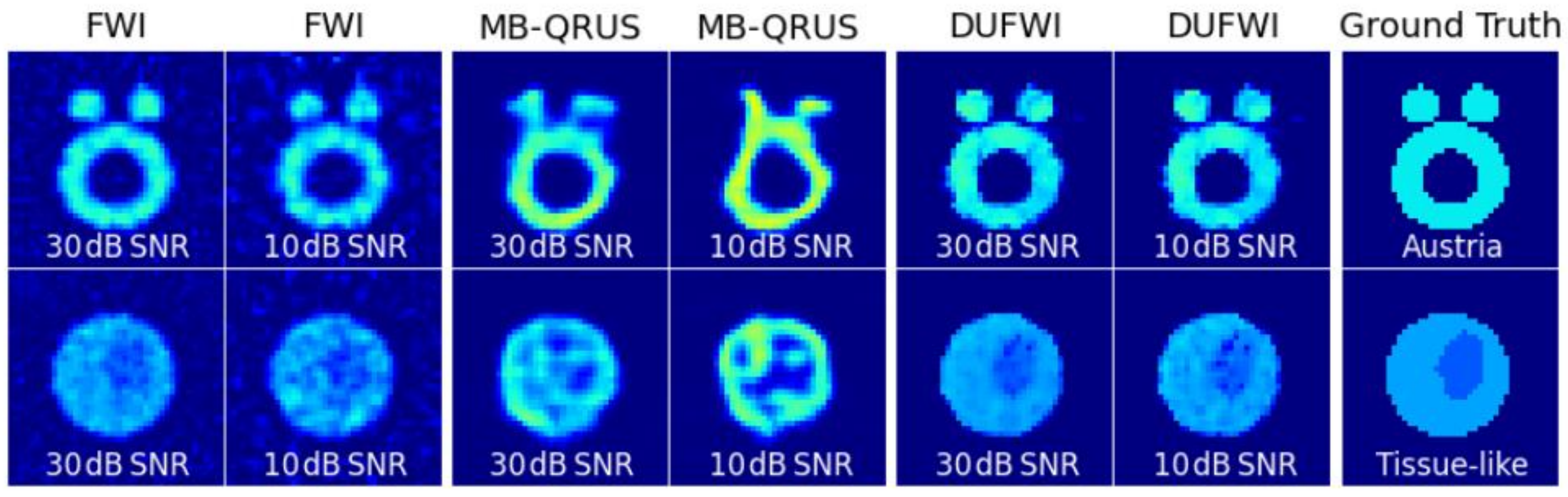
$\mathbf{s}_k^{(i)} \rightarrow$ Compute Gradients $\{\mathbf{g}_k^{(i)}\}$ $\rightarrow$ Train $\rightarrow \mathbf{s}_{k+1}^{(i)}$

$(\mathbf{s}_k^{(i)}, \mathbf{g}_k^{(i)}) \rightarrow \mathbf{s}_{k+1}^{(i)}$ $\quad \mathcal{L}(\theta_k) = \frac{1}{M}\sum_i \left\|\mathbf{s}_{gt}^{(i)} - \mathbf{s}_{k+1}^{(i)}\right\|_2^2,$

5. Results

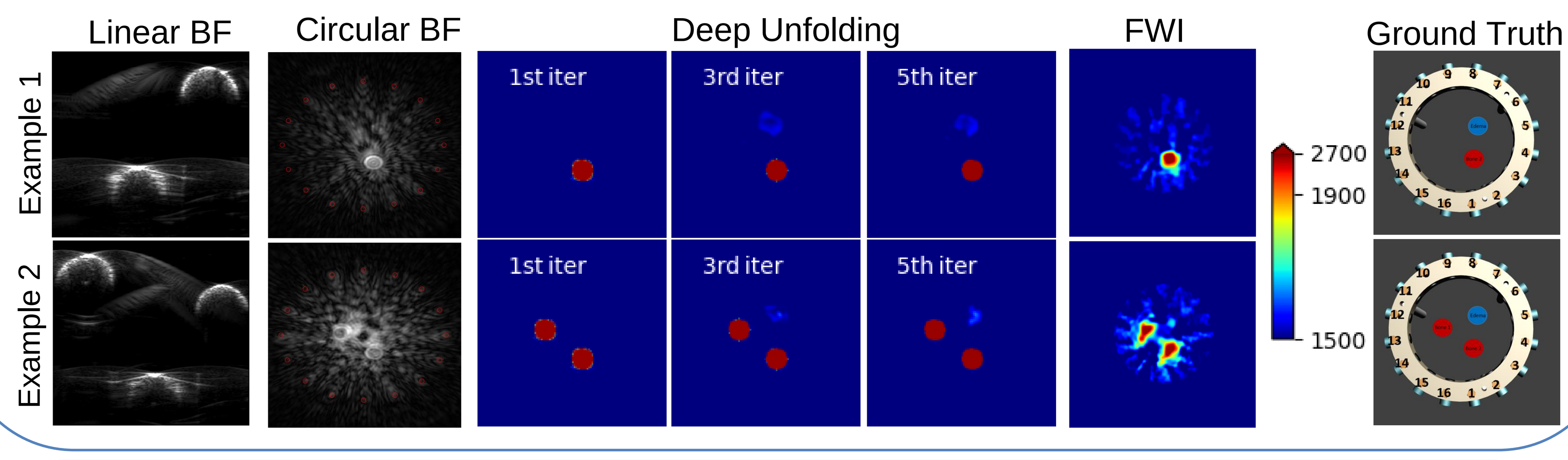


- Outperforming classical FWI and MB-QRUS.
- Less forward iteration than FWI and much faster.
- Better generalization and robustness to noise



6. Hardware Results

- DUFWI able to recover real-world hardware scans of bone and edema



7. Conclusion

- **DUFWI improves reconstruction accuracy** compared to classical FWI and MB-QRUS, particularly under noisy conditions.
- **Faster convergence** with significantly fewer iterations than traditional FWI, making it more practical for real-time imaging.
- **Better generalization** on out-of-distribution samples, demonstrating robustness across different datasets.
- **Efficient block-by-block training** avoids repeated wave simulations, making the method computationally viable.
- **Potential for real-world biomedical applications**