AI-Driven Seismic Frequency-Domain Wavefield Reconstruction For Efficient 2-D Seismic Imaging

Jiahua Zhao

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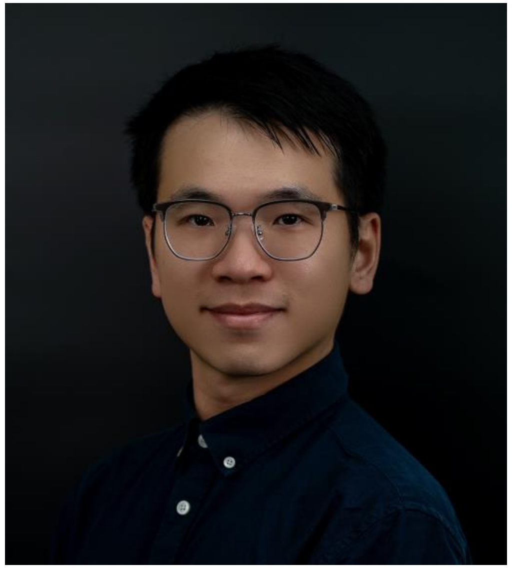
The Cyprus Institute — Research · Technology · Innovation

Delphi Consortium

TU Delft

University of Cyprus

Self Introduction



Jiahua Zhao (CyI)

PhD student (2nd year) in Computational Science.

PhD Project:
- ➢ Improving the efficiency and quality of 3-D seismic imaging addressing HPC / AI aspects.

PhD programme:
- ➢ ENGAGE (Enabling the next generation of computational physicists and engineers) under the Marie Skłodowska-Curie actions (MSCA) COFUND scheme.

Geophysics
Seimic Imaging

Eric Verschuur (TU Delft)
Supervisor

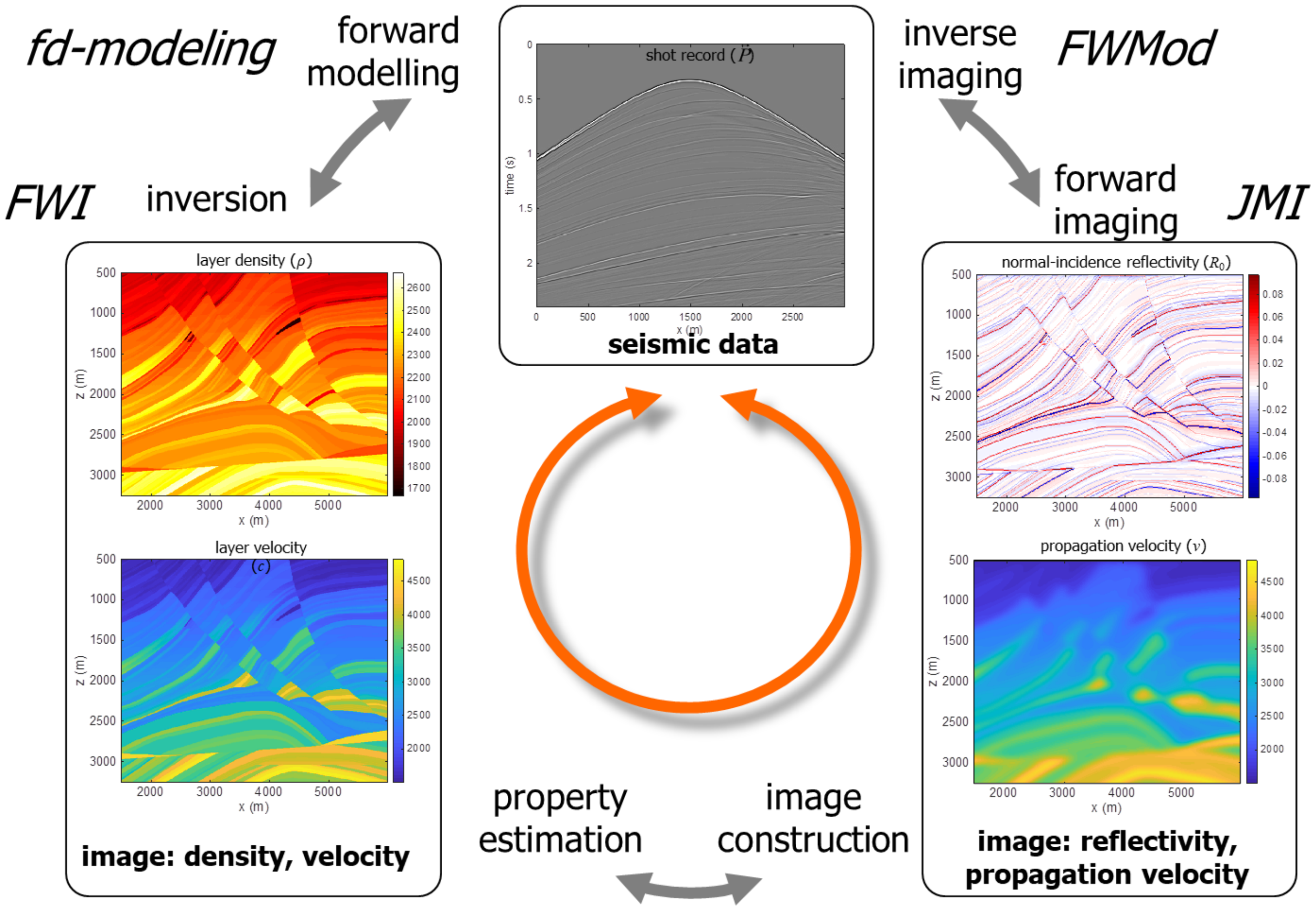
Scientific Computing
Machine Learning

Nikos Savva (CyI / UCY)
Co-Supervisor

Outline

- Brief Introduction
- Methodology
- Experiments and Results
- Conclusion and Future Works

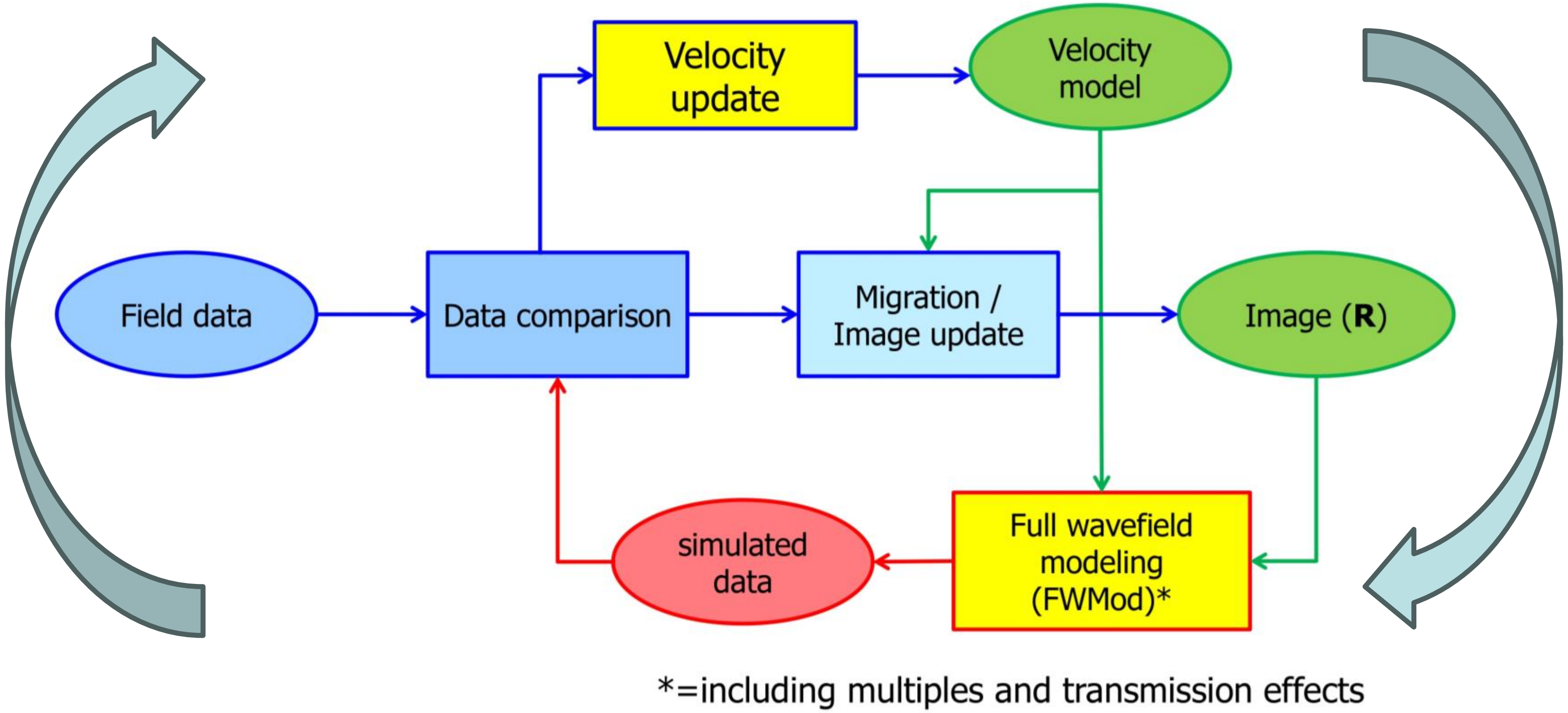
Introduction to Joint Migration Inversion



Joint Migration Inversion (JMI) is an innovative geophysical solution that ingeniously integrates the dual core processes of velocity model construction and seismic imaging into a unified algorithmic framework (*Verschuur et al., 2016; Sun et al., 2020*).

JMI integrates velocity modeling with the imaging process to jointly optimize velocity and reflectivity, whereas Full Waveform Inversion (FWI) focuses on directly inverting subsurface properties from full waveform data.

Introduction to Joint Migration Inversion



Closed-loop process: iterate until modeled datafits the measurements

In terms of computation process, JMI is divided into reflectivity update and velocity (slowness) update, and the two are similar in algorithm process.

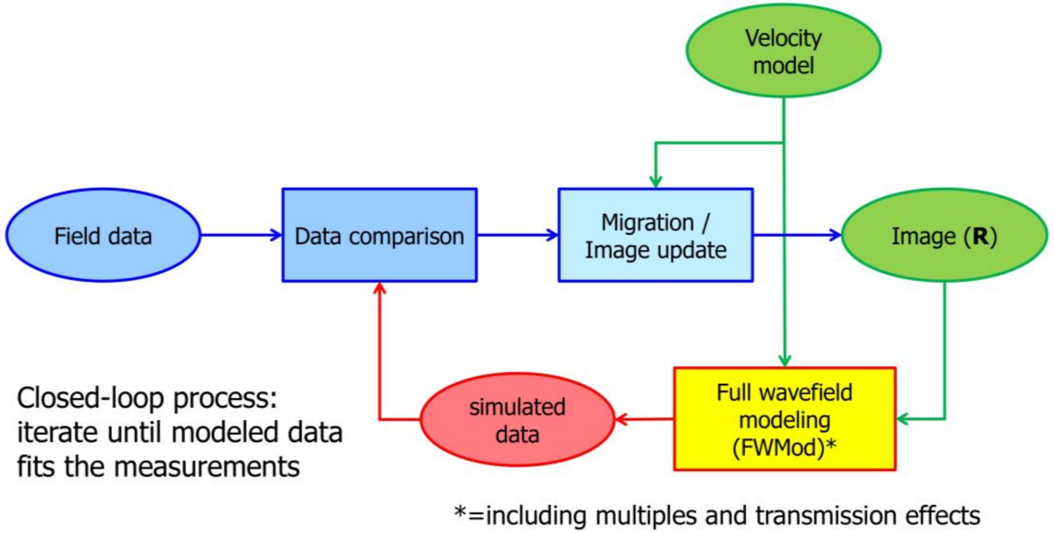
In practice, JMI adopts a unique migration technique known as Full Wavefield Migration (FWM) (*Berkhout, 2014b*).

Introduction to Full Wavefield Modeling

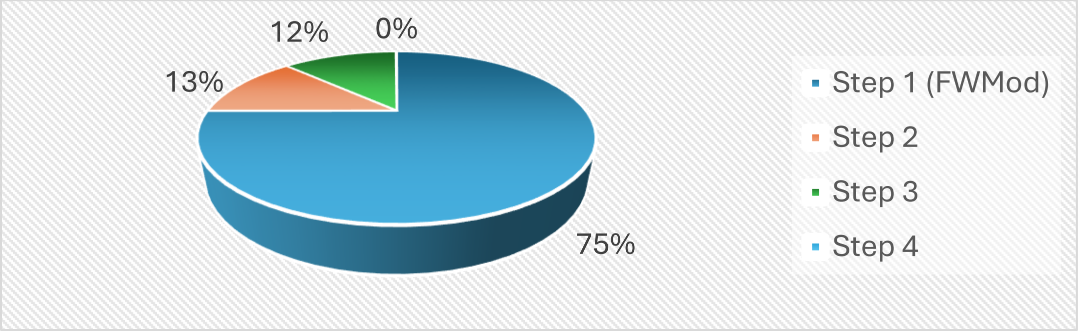
FWM takes a model-driven approach to estimating its modelling operators, basing them on a reflectivity and a velocity model through a Full Wavefield Modelling (FWMod) algorithm (*Berkhout, 2014a*).

For the reflectivity update (*Staal, 2015*):

1. Update wavefelds within the chosen frequency band, based on the most recent model estimates (one roundtrip) and determine the new residual.
2. Calculate and optimise update direction for reflectivity (one roundtrip).
3. Calculate the linearised wavefield perturbation associated to the update direction, within the chosen frequency band (one roundtrip).
4. Calculate scaling parameter for the update direction and finally update the reflectivity model.



*FWMod faces increased computational and memory demands in 2-D and 3-D, leading to high costs and reliance on computation resources.



Our Motivation and Ideas

What is program performance optimization?

Program performance optimization is the process of modifying software so it runs more efficiently: using less time, memory, power, or other resources, while preserving its intended functionality. (en.wikipedia.org)

What are the optimization methods?

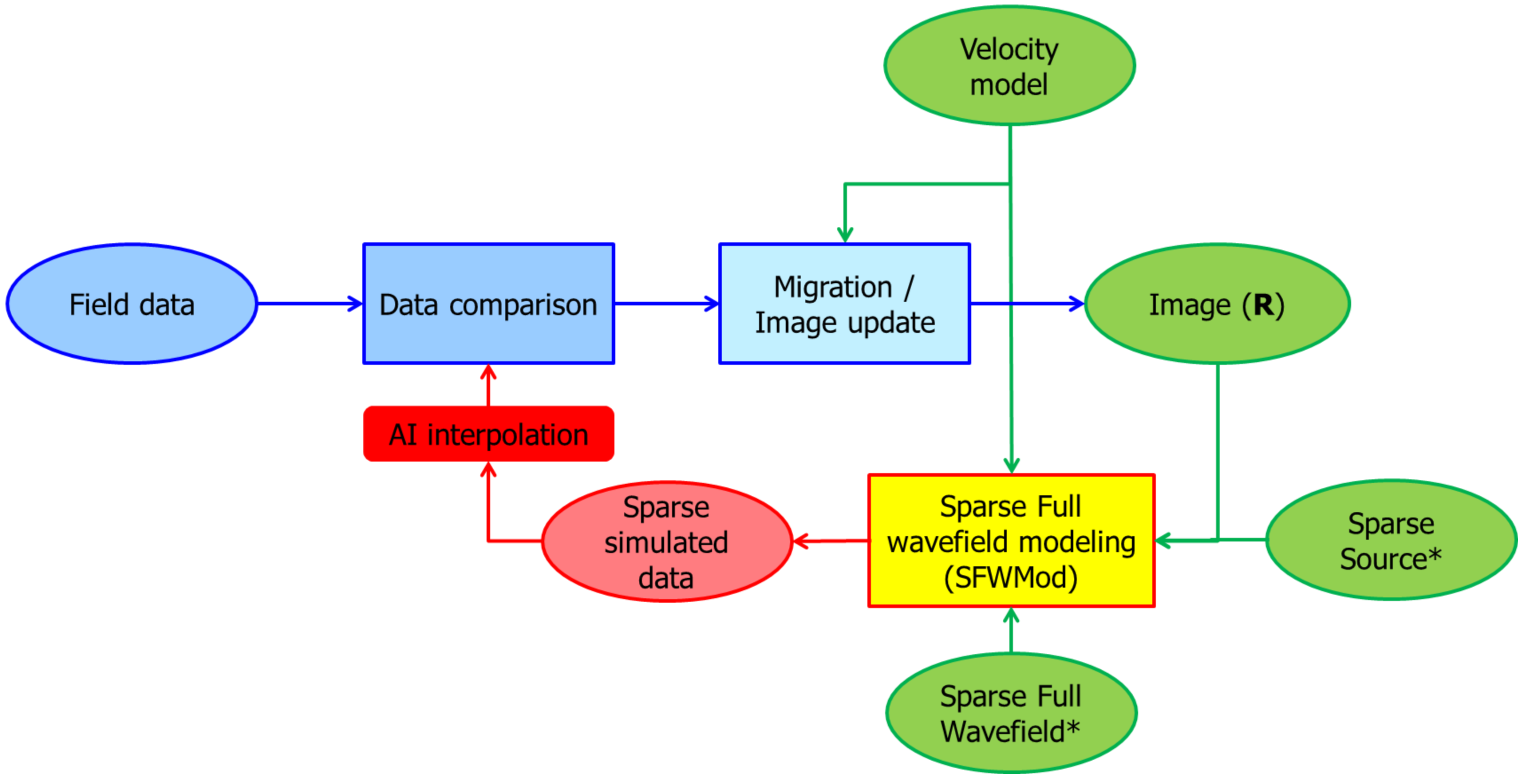
- **Software level:**
  - Reduce the amount of computation (data)
  - Use a fast convergence method
  - Accelerate correlation computations using the acceleration library (e.g. cuFFT)
- **Hardware level:**
  - Use CPUs with the latest architecture
  - Use GPUs for computation

Misunderstanding：

performance optimization ≠ improve accuracy / resolution

The efficiency of computation is increased as much as possible while ensuring the accuracy and resolution are close to the numerical JMI.

Our Motivation and Ideas



*Traditional FWMod method use complete wavefield and source data by default, while the AI-driven FWMod method uses sparse data as input.

- To tackle FWMod computational load, we utilize separate frequency processing: Using direct computation for some frequencies and frequency interpolation.
- We use a trained neural network model to assist JMI in the modeling part: model few frequencies and interpolate the rest via Machine Learning.

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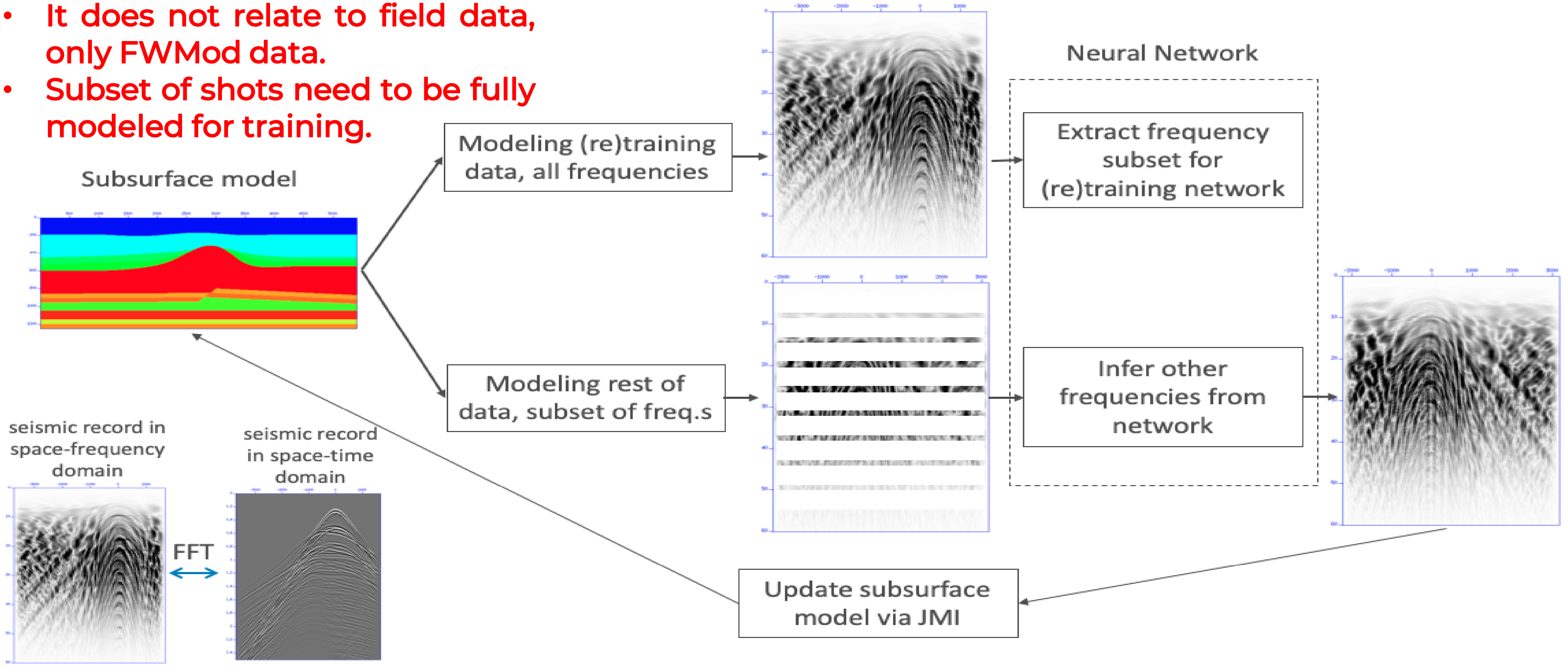
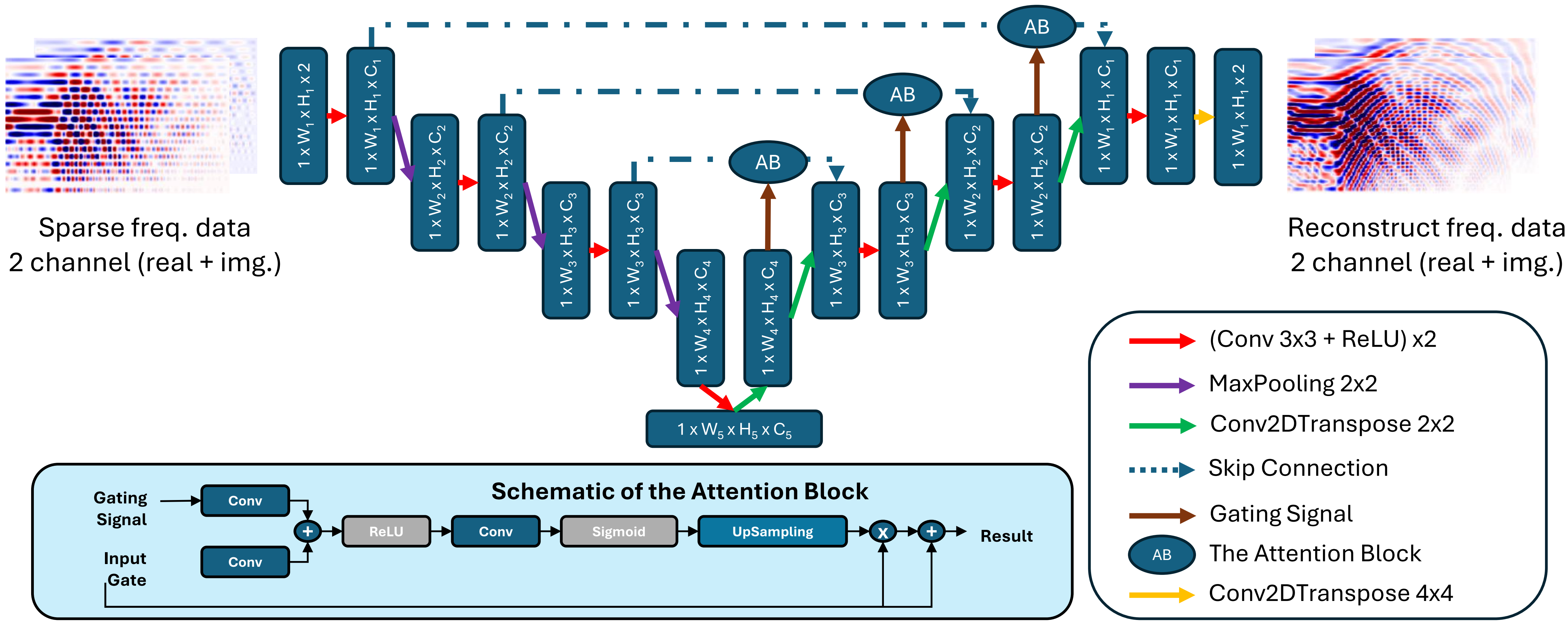
Our Acceleration Kernel Overview

- It does not relate to field data, only FWMod data.
- Subset of shots need to be fully modeled for training.



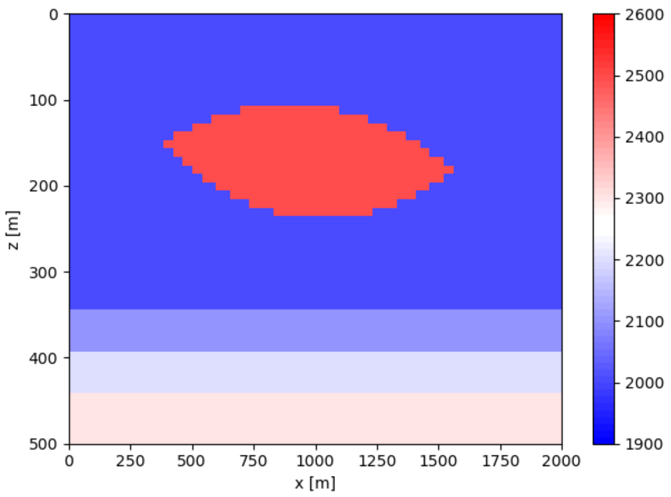
Neural Network Design: Attention U-Net

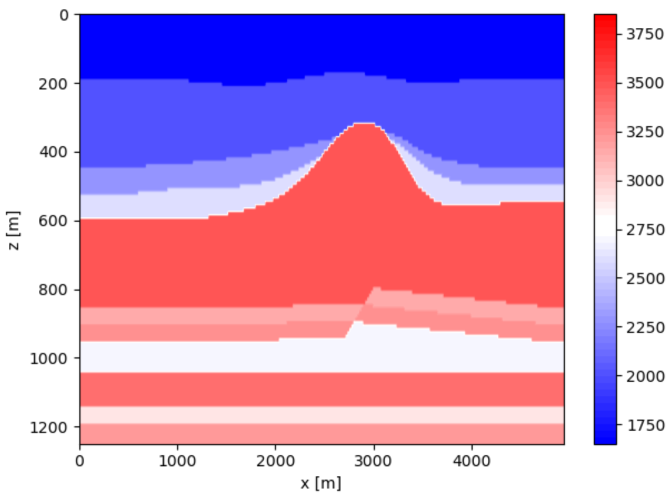


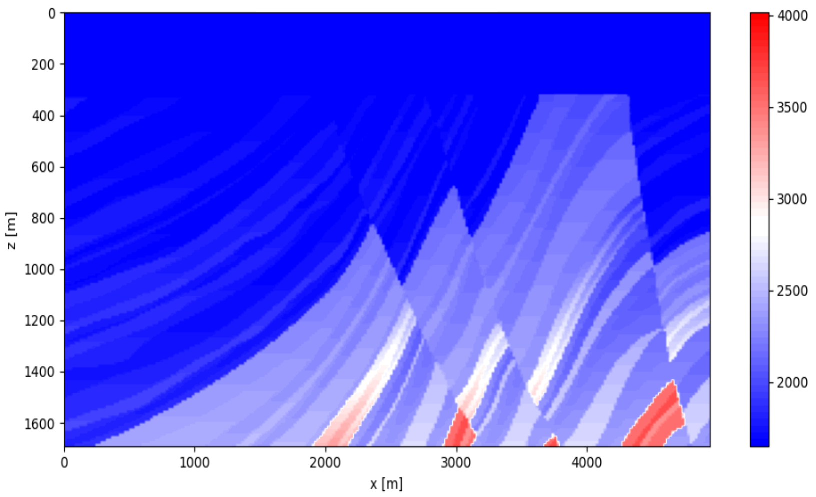
We use an adapted AU-Net architecture (*Oktay et al. 2018*), a refined deep convolutional neural network that incorporates attention gates to enhance reconstruction precision and robustness by focusing on key features.

Introduction to the Synthetic Data

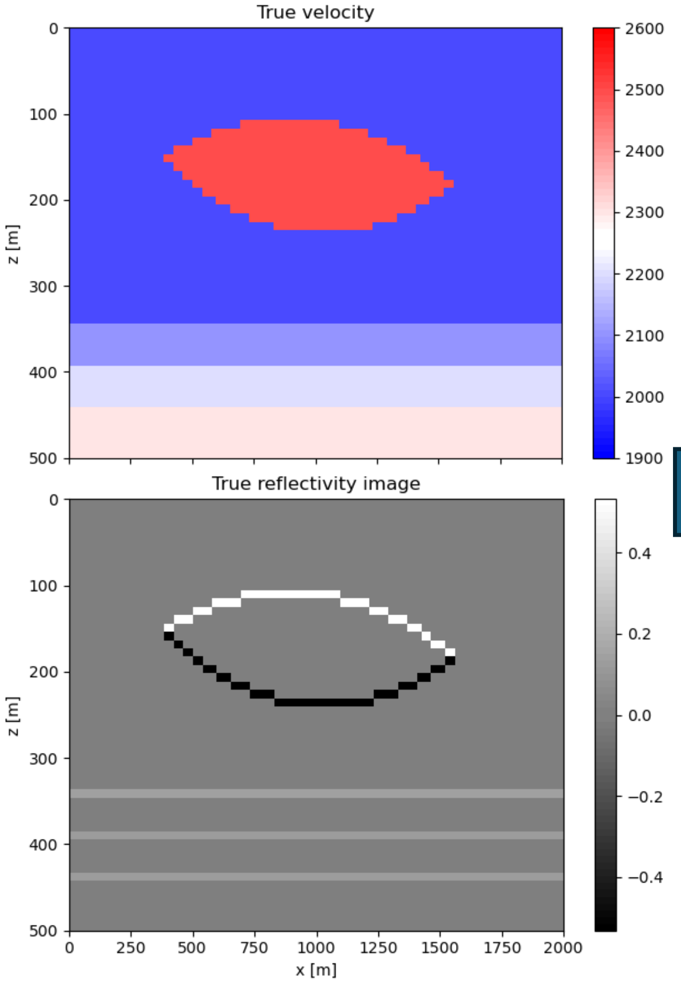
	2-D Lens-shaped Model (*Staal, 2015*)	2-D Salt Model (*Berkhout and Verschuur, 2006*)	2-D Marmousi Model (*Brougois et al., 1990*)
nx, dx, nz, dz	104, 20, 51, 10	248, 20, 126, 10	248, 20, 170, 10
nt, dt	256, 0.004	300, 0.008	300, 0.008
fmin, fmax, f0	1, 40, 20	1, 40, 15	1, 40, 15
nsrc	104	248	248
Wavelet form	The Ricker wavelet	The Ricker wavelet	The Ricker wavelet





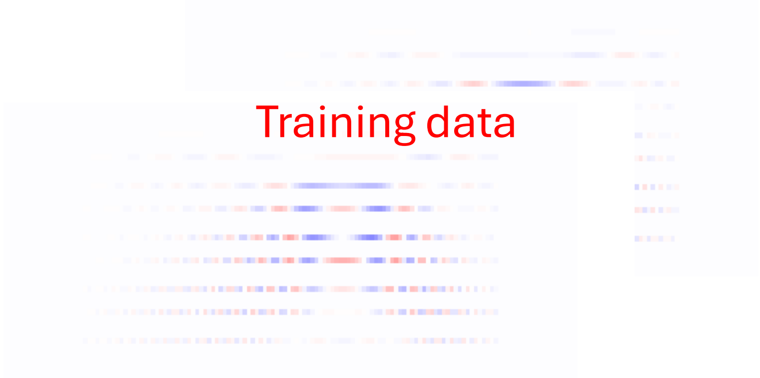


Dataset Preparation: 2-D Lens-shaped Model



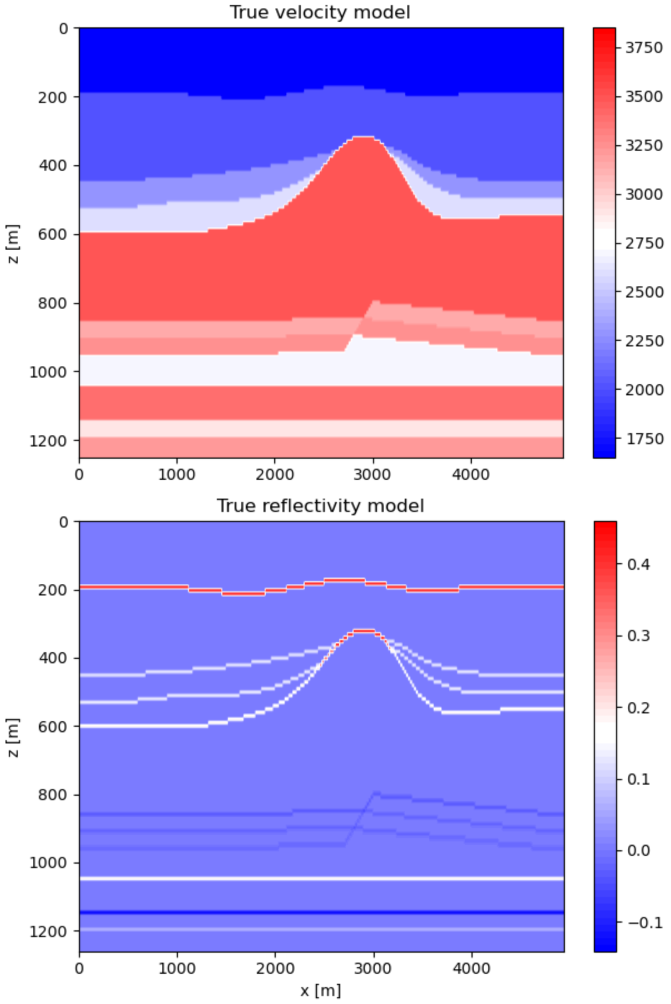
FWMod
(Dataset Generation)

1. Generate complete wavefield data in frequency domain;
2. Randomly select 50% of the frequencies to delete, and retain the remaining frequencies to form sparse data;
3. Defined the complete data as labels.
4. Pre-processing including normalization via the hyperbolic tangent function.



3-D (nx, nf, 2 channels) samples (1 - 40 Hz), ultimately generating a total of 10,000 samples.

Dataset Preparation: 2-D Salt Model



FWMod
(Dataset Generation)

1. Generate complete wavefield data in frequency domain;
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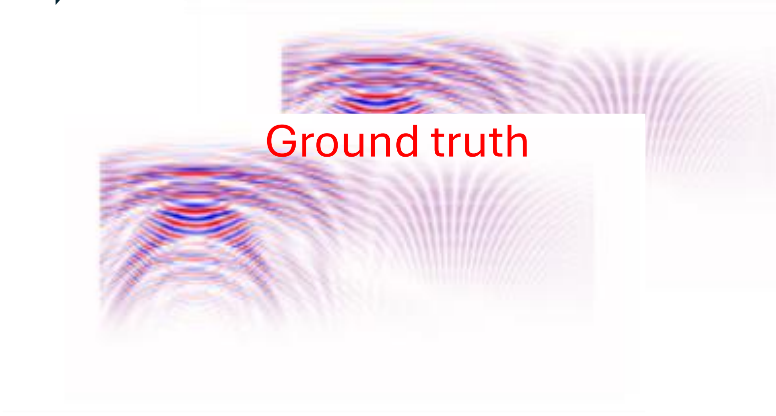
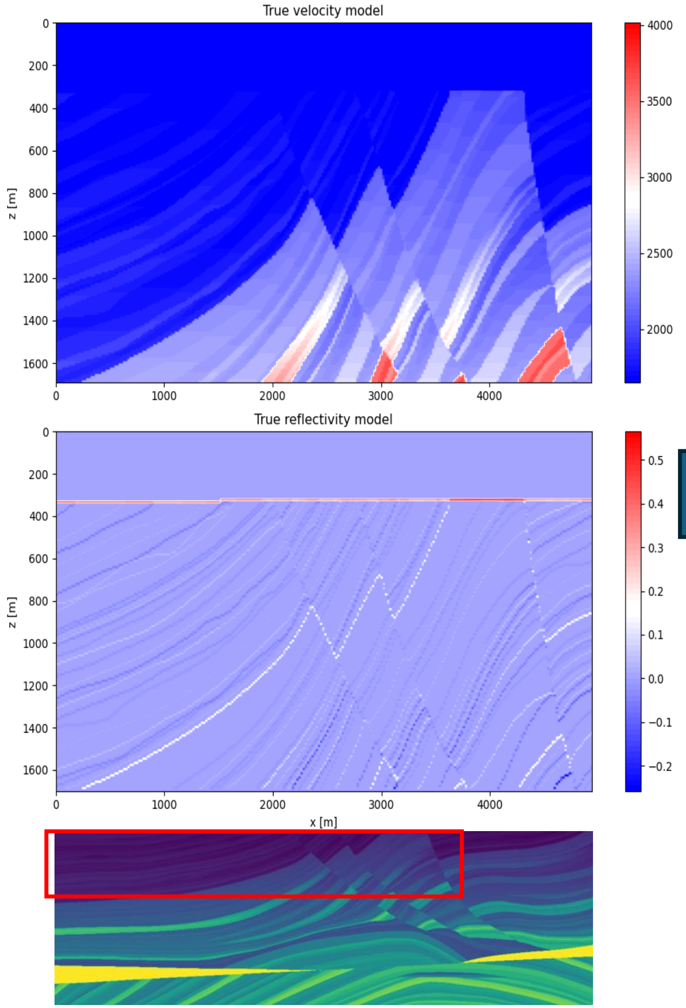
4. Pre-processing including normalization via the hyperbolic tangent function.

3-D (nx, nf, 2 channels) samples (1 - 40 Hz), ultimately generating a total of 10,000 samples.



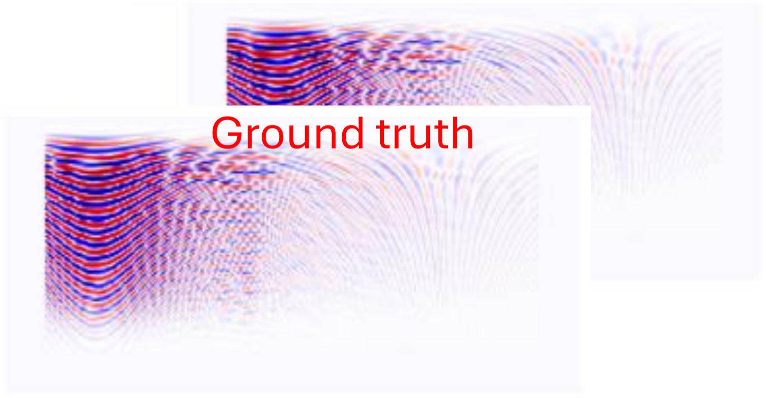
Dataset Preparation: 2-D Marmousi Model



FWMod
(Dataset Generation)

1. Generate complete wavefield data in frequency domain;
2. Randomly select 50% of the frequencies to delete, and retain the remaining frequencies to form sparse data;
3. Defined the complete data as labels.
4. Pre-processing including normalization via the hyperbolic tangent function.

3-D (nx, nf, 2 channels) samples (1 - 40 Hz), ultimately generating a total of 10,000 samples.



Preparation before Training

SimEA (hosting on Cyclone)
Bespoke system created for large projects

The NN model is trained (data parallel) on 10,000 samples (each velocity model) using one GPU node (4 GPUs):

- 2x 24-core sockets with Intel Xeon Gold 6330
- **4x NVIDIA A100-SXM4 40GB GPUs**
- 512 GB memory

Building NN model with Keras framework (TensorFlow backend)

TensorFlow + Keras NVIDIA CUDA

Cyclone HPC*: a hybrid CPU and GPU system

*https://hpcf.cyi.ac.cy/

Preparation before Training

Metrics To Evaluate Machine Learning Model: In addition to **Mean Absolute Error (L1 Loss)**, the quality of predicted data is evaluated by **Structural Similarity Index (SSIM)** and **Peak Signal-to-Noise Ratio (PSNR)**, which can provide an objective evaluation of data reconstruction quality and similarity.

L1 Loss

This gives an average measure of the absolute difference between the two images.

$$\mathrm{MAE} = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} |I_1(i,j) - I_2(i,j)|$$

SSIM

It is a measure of the similarity between two images based on luminance, contrast, and structure.

$$\mathrm{SSIM}(X,Y) = \frac{(2\mu_X\mu_Y + C_1)(2\sigma_{XY} + C_2)}{(\mu_X^2 + \mu_Y^2 + C_1)(\sigma_X^2 + \sigma_Y^2 + C_2)}$$

PSNR

It is a metric used to measure the quality of image reconstruction by comparing the maximum possible value of the image to the mean squared error between the original and reconstructed images.

$$\mathrm{PSNR} = 10 \log_{10} \left(\frac{(L^2)}{\frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} [I_1(i,j) - I_2(i,j)]^2} \right)$$

Preparation before Training

Hyper-params	Settings	Notes
Epochs	200	
Batch	32	Global batch size: 128
Learning Rate	0.01	ReduceLR
Validation Split Rate	0.2	80% for training; 20% for validating
Scheduler & Optimizer	**Settings**	**Notes**
Reduce Learning Rate	Monitor: min validation MAE	Min Learning Rate: 0.00001
Early Stopping	Monitor: min validation MAE	Patience: 10 Epochs
Training data shuffle		
Adam		Default settings from TensorFlow
Loss Function	**Settings**	**Notes**
Mix Loss	**0.5 * loss in time domain + 0.5 * loss in freq. domain**	**Time loss + Freq. loss**

$$MixMAE = 0.5 * \left(\frac{1}{n}\sum_{i=1}^{n}\left|y_{true,i} - y_{pred,i}\right|\right) + 0.5 * \left(\frac{1}{n}\sum_{i=1}^{n}\left|ifft(y_{true,i}) - ifft(y_{pred,i})\right|\right)$$

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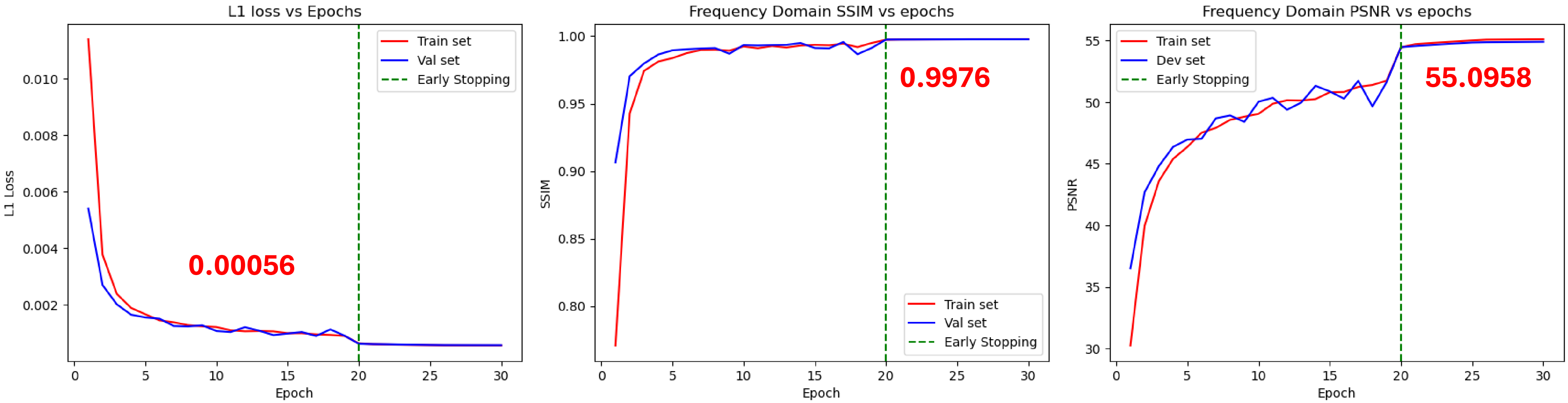
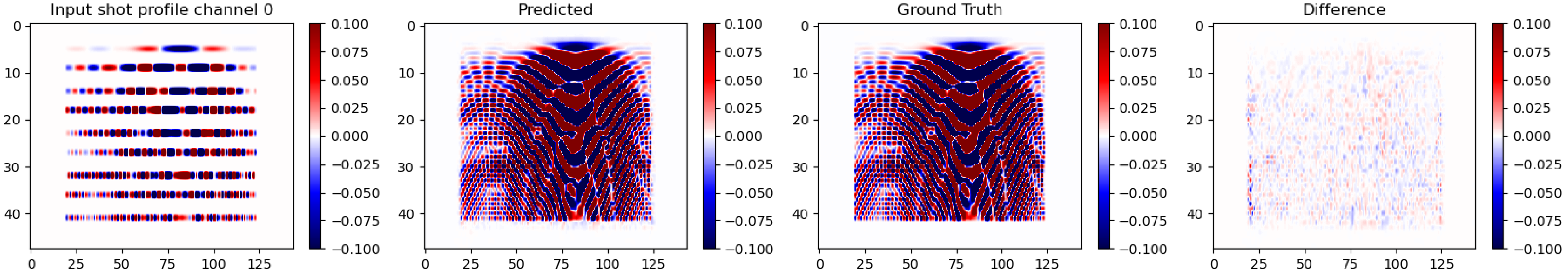
Training Results and Evaluation



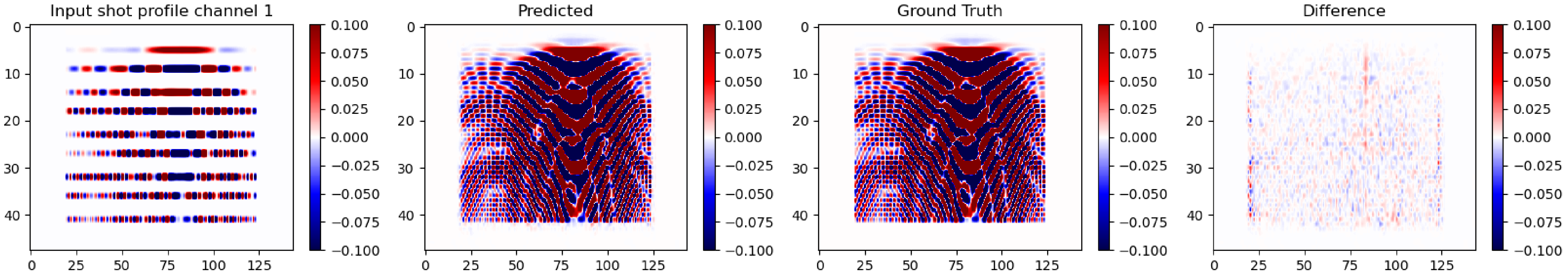
The training took 30 epochs (14 seconds) to complete.

Training Results and Evaluation

Real Part (2-D lens-shaped model)

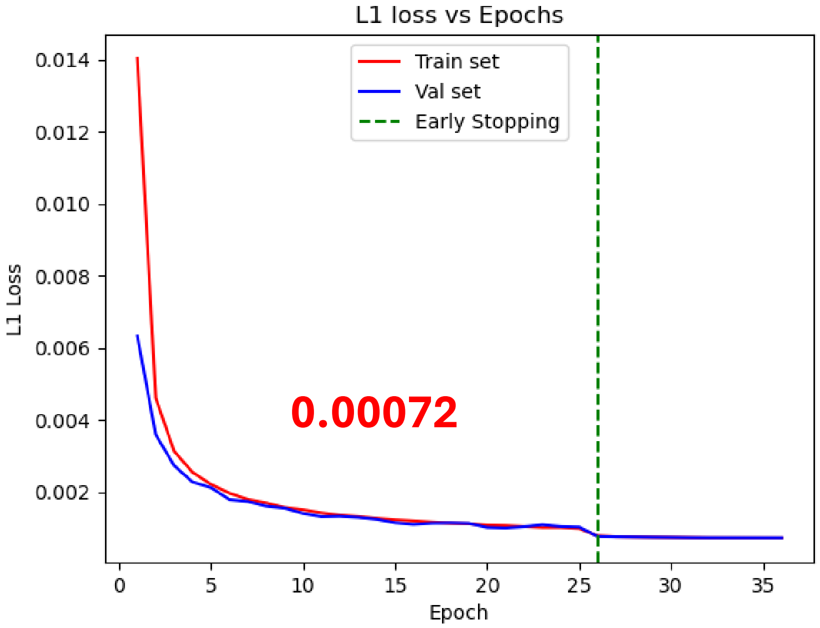


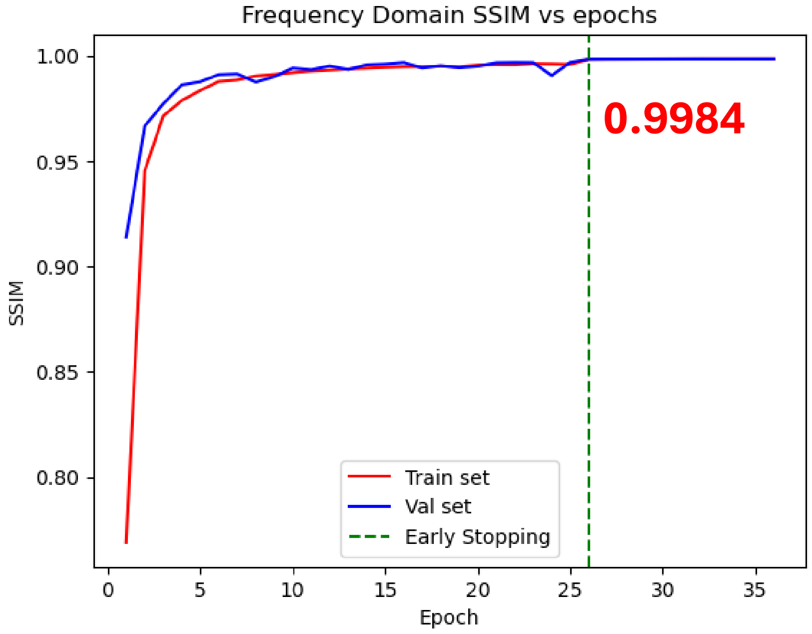
Imag. Part (2-D lens-shaped model)

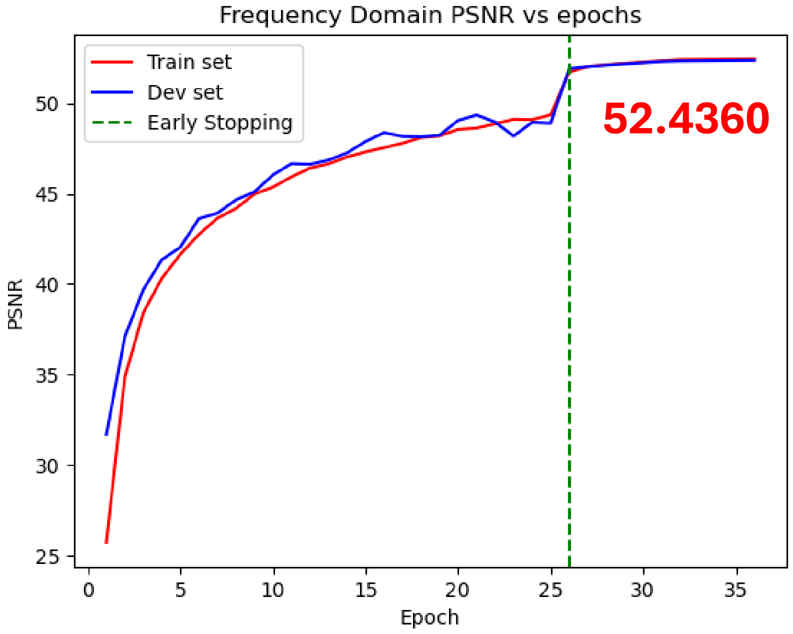


Testing Dataset: AvgMAE: 6.7011e-04 - AvgSSIM: 0.9968 - AvgPSNR: 54.0424

Training Results and Evaluation



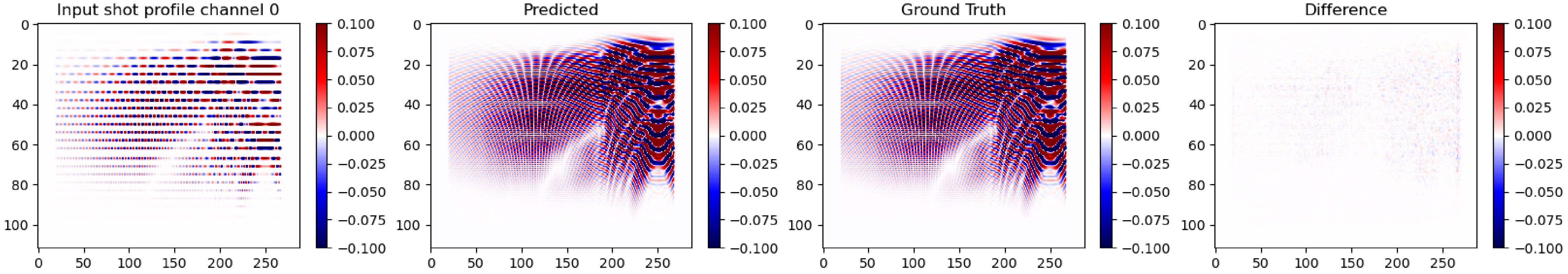




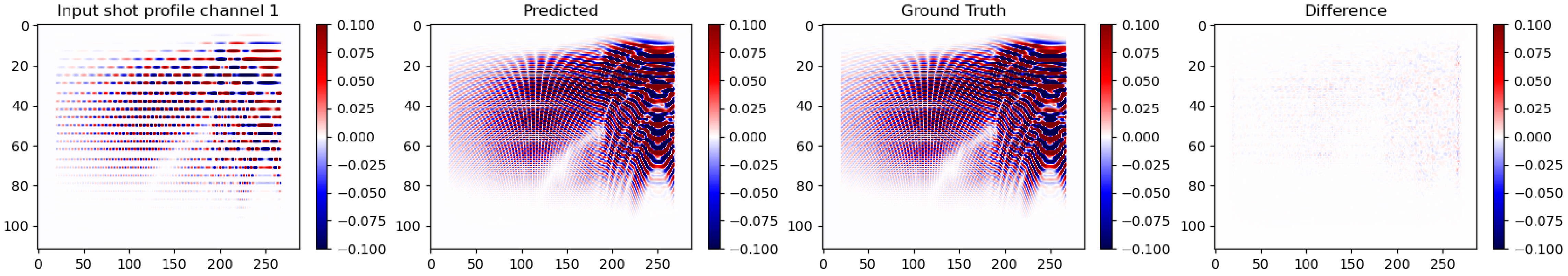
The training took 36 epochs (252 seconds) to complete.

Training Results and Evaluation

Real Part (2-D Salt Model)

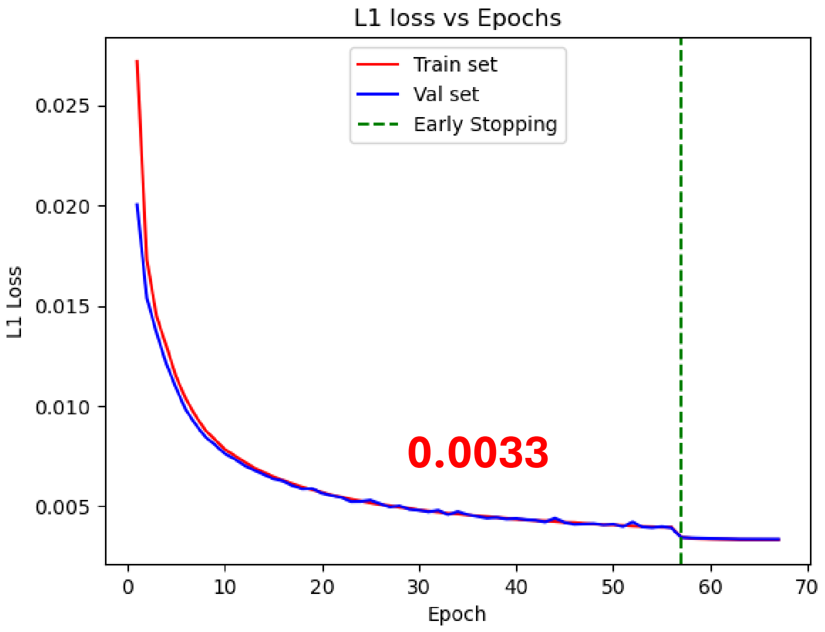


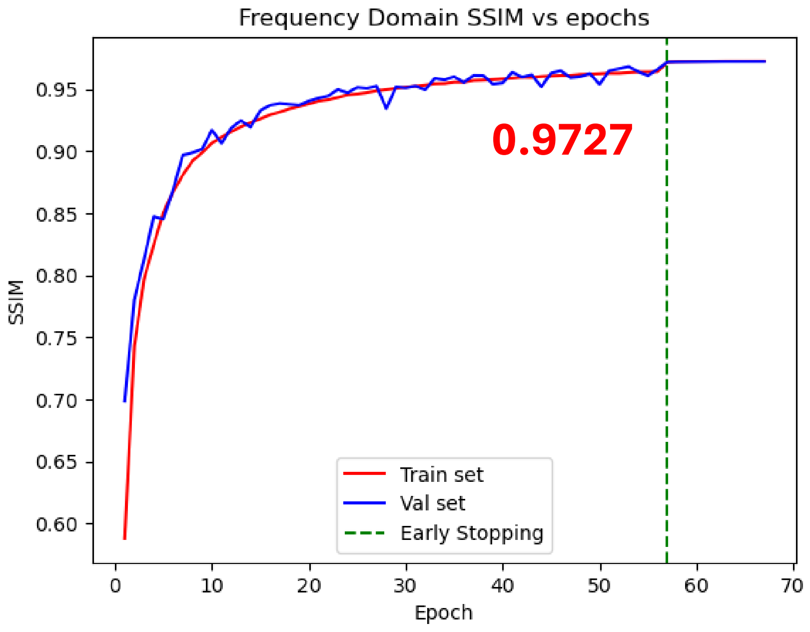
Imag. Part (2-D Salt Model)

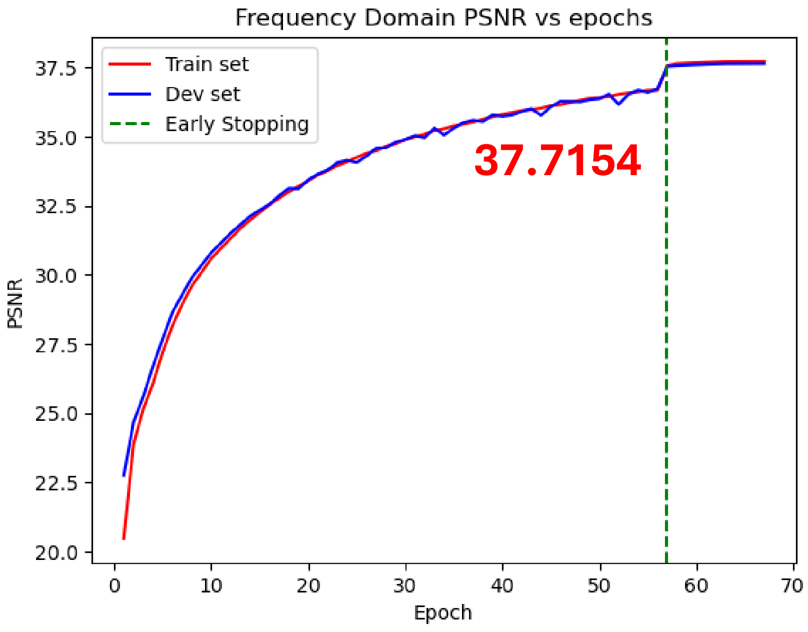


Testing Dataset: AvgMAE: 6.8312e-04 - AvgSSIM: 0.9986 - AvgPSNR: 52.7893

Training Results and Evaluation



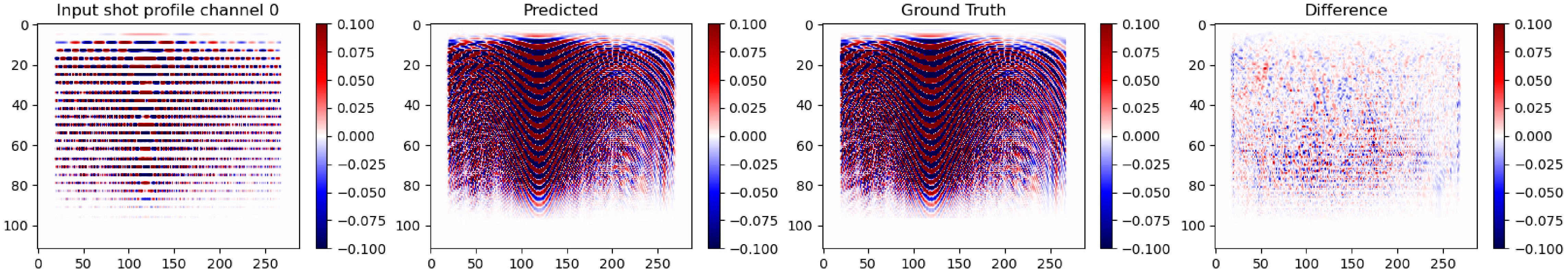




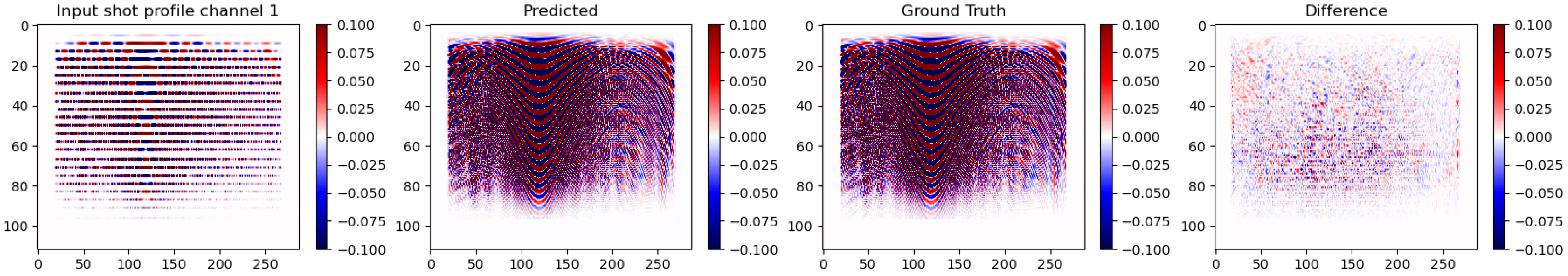
The training took 67 epochs (469 seconds) to complete.

Training Results and Evaluation

Real Part (2-D Marmousi Model)



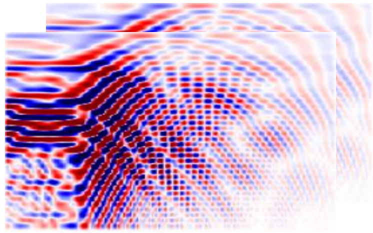
Imag. Part (2-D Marmousi Model)

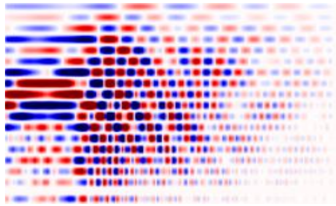


Testing Dataset: AvgMAE: 0.0028 - AvgSSIM: 0.9765 - AvgPSNR: 39.5327

Preparation before Inference

Preparation before Inference





Velocity model

Image (**R**)

Sparse Full wavefield modeling (SFWMod)

Sparse Source

Sparse Full Wavefield

Sparse simulated data

AI interpolation

Reconstruction data

1x NVIDIA A100-SXM4 40GB GPU

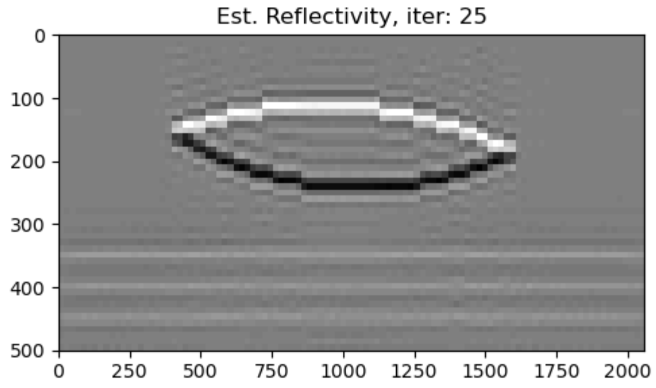
NumPy

CuPy

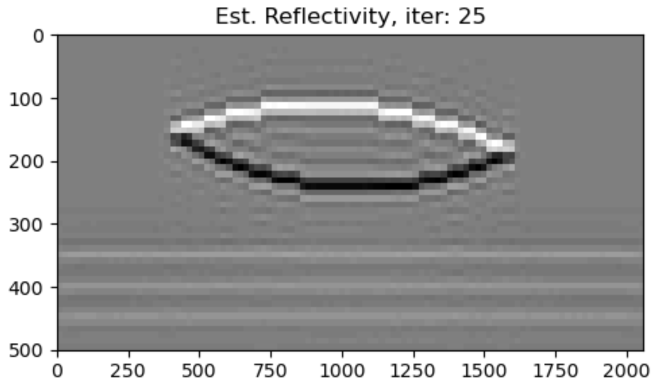
DLPack

TensorFlow

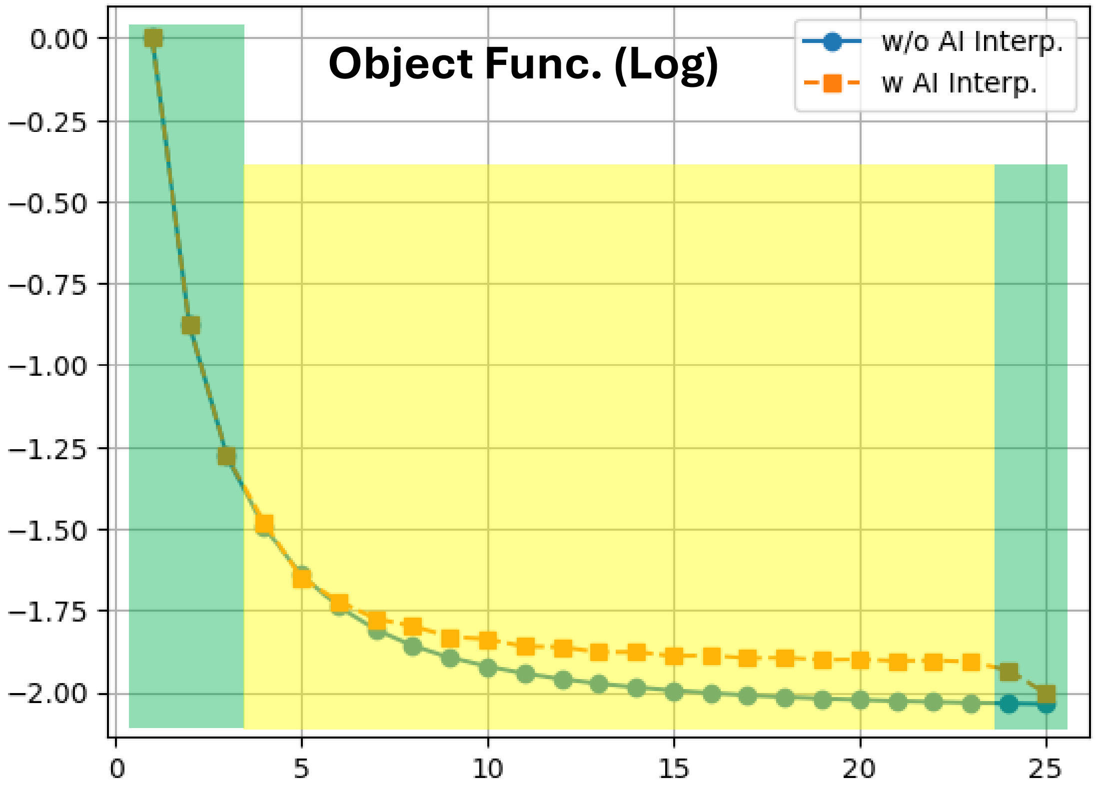
Numerical Experiment for Reflectivity Update



AI-improved JMI

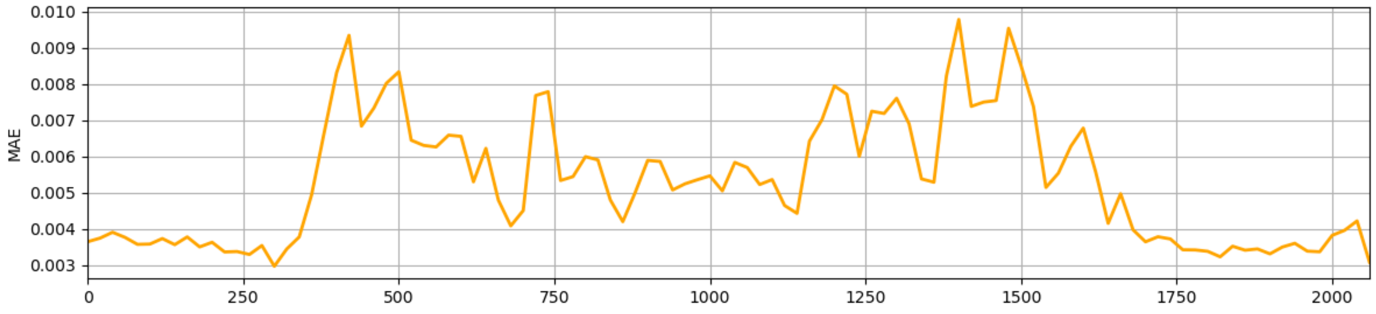


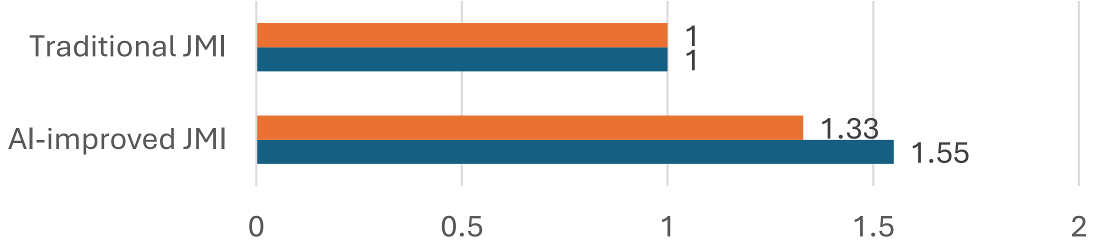
Traditional JMI



Numerical Method

AI Interpolation



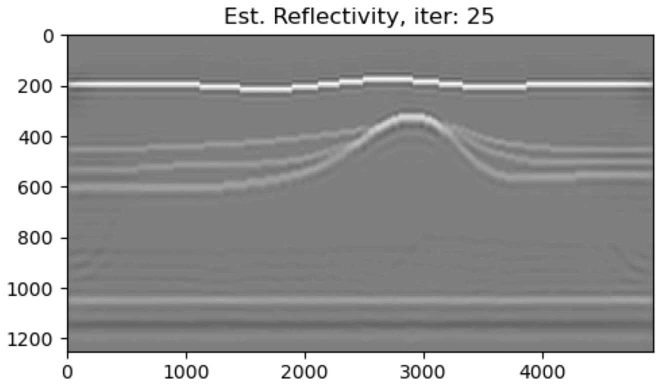


Speedup

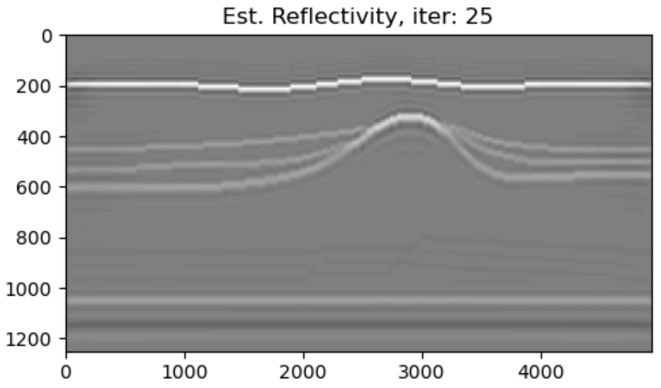
Full Interation

Per Interation

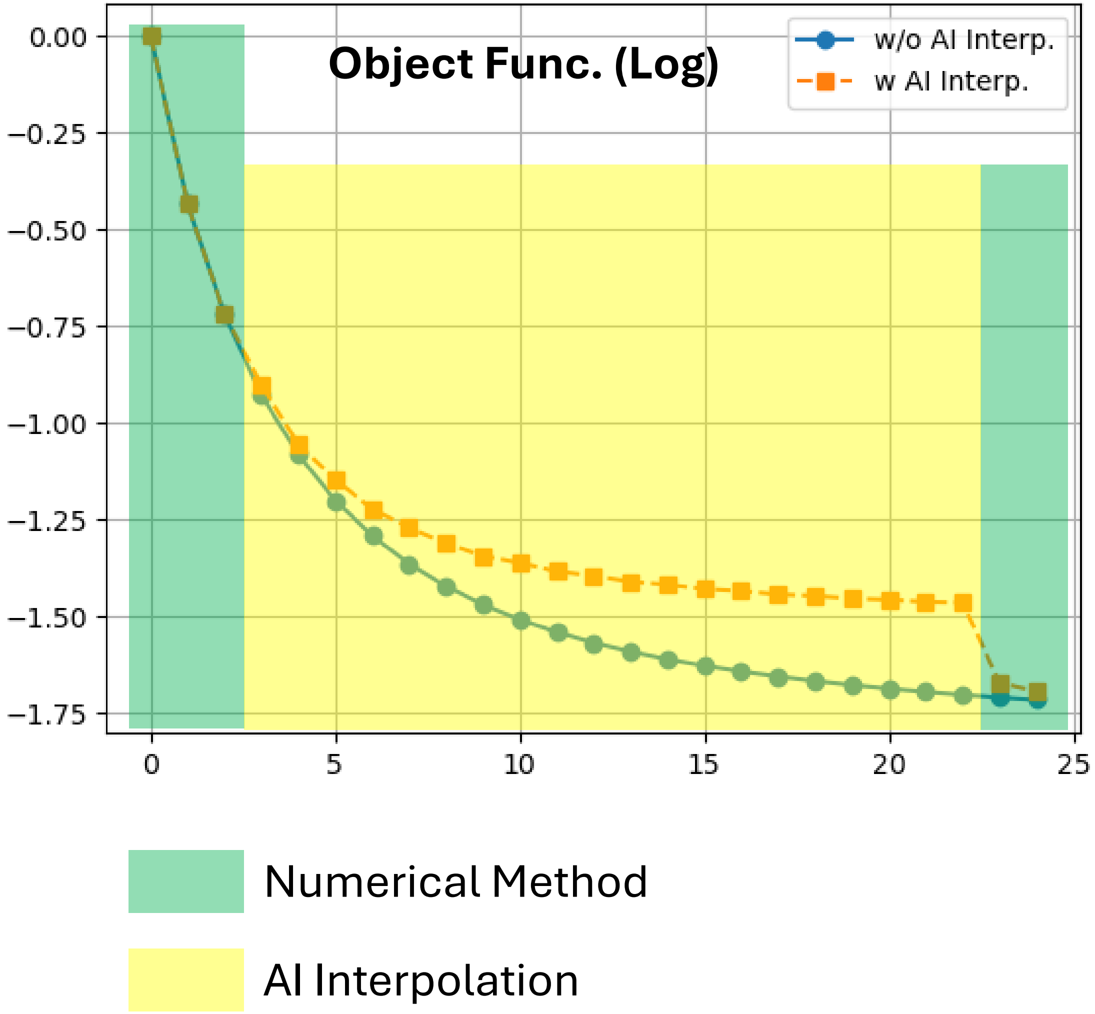
Numerical Experiment for Reflectivity Update

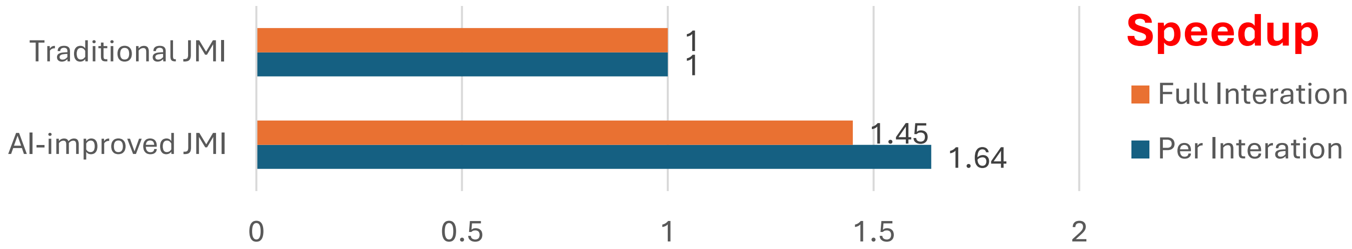


AI-improved JMI

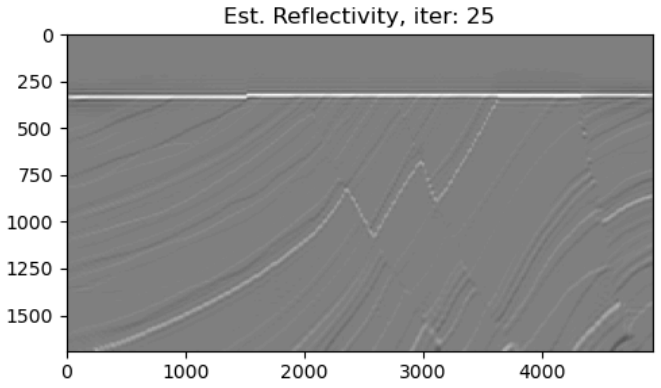


Traditional JMI

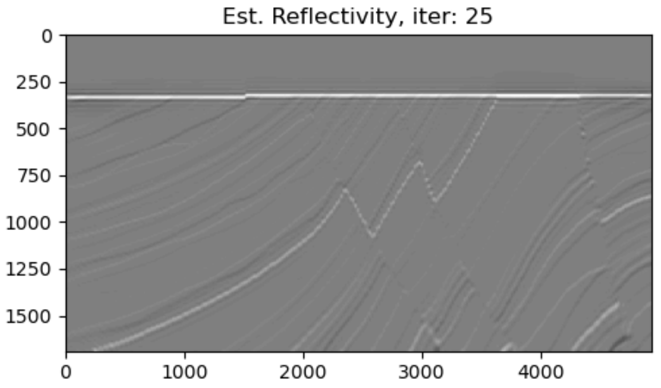




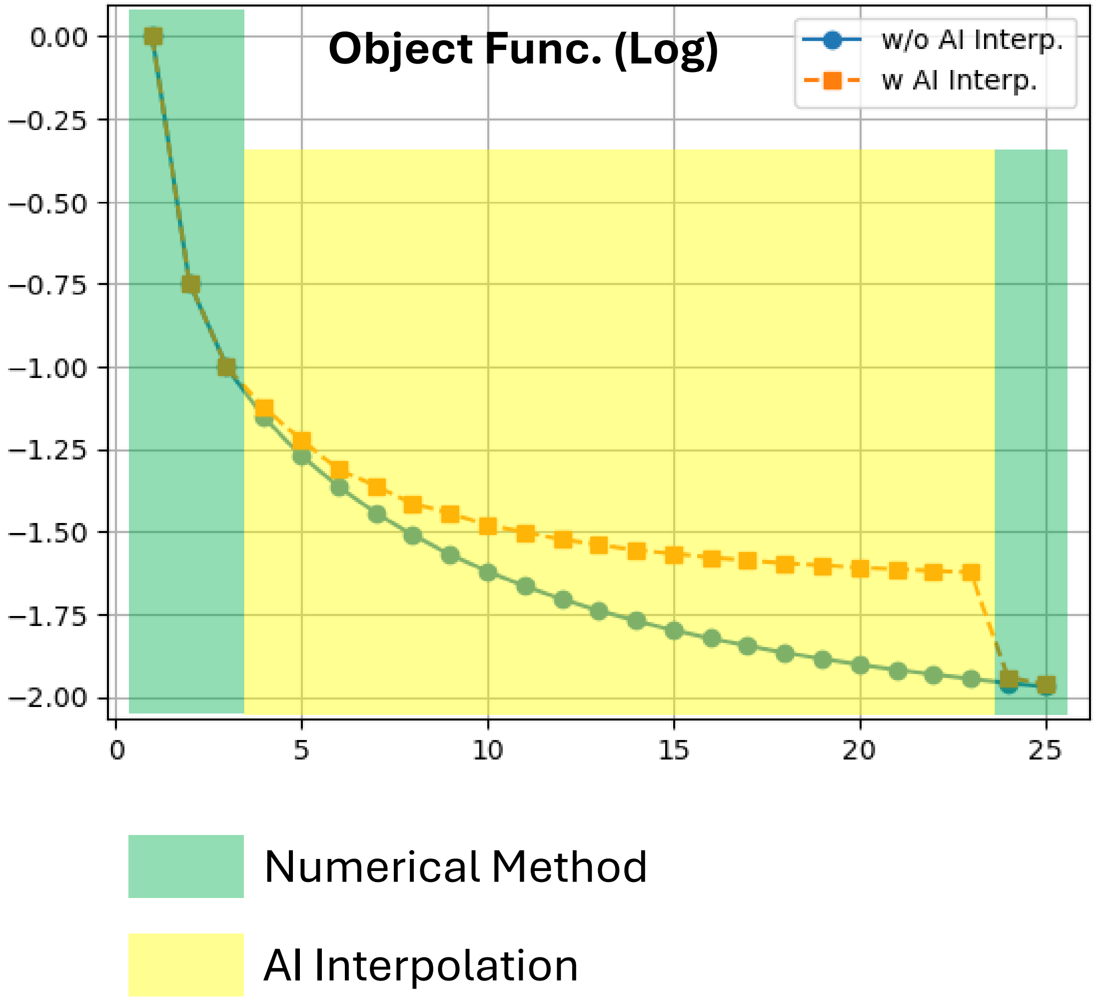
Numerical Experiment for Reflectivity Update

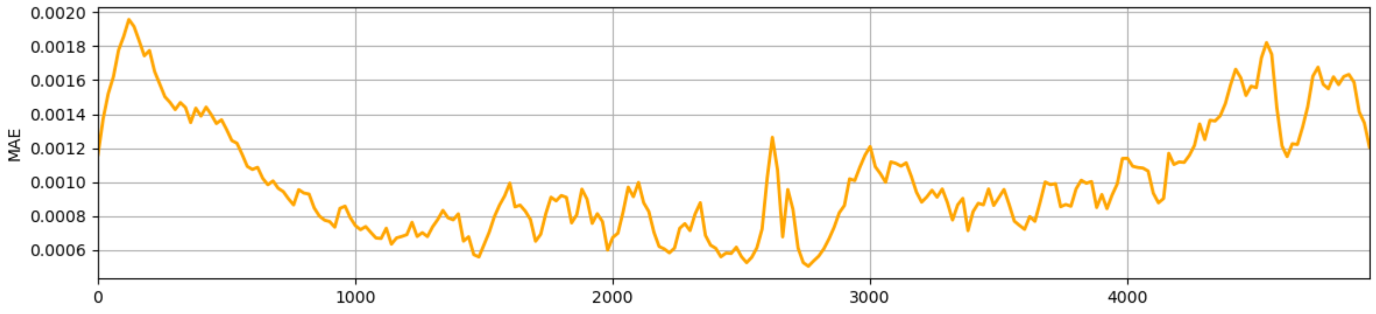


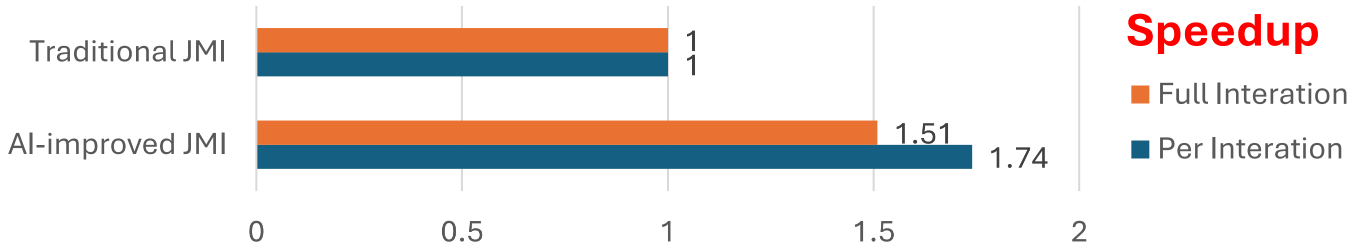
AI-improved JMI



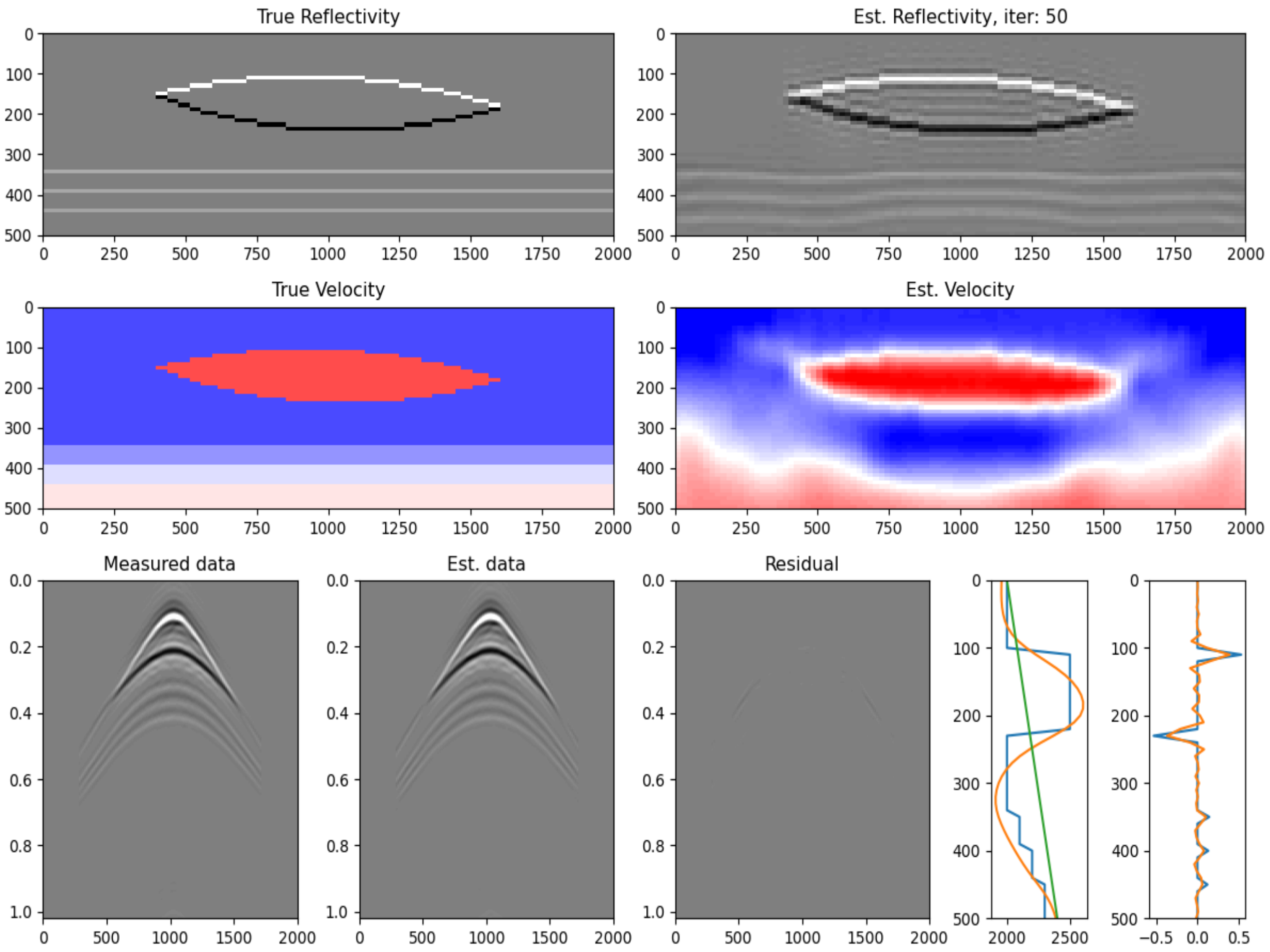
Traditional JMI



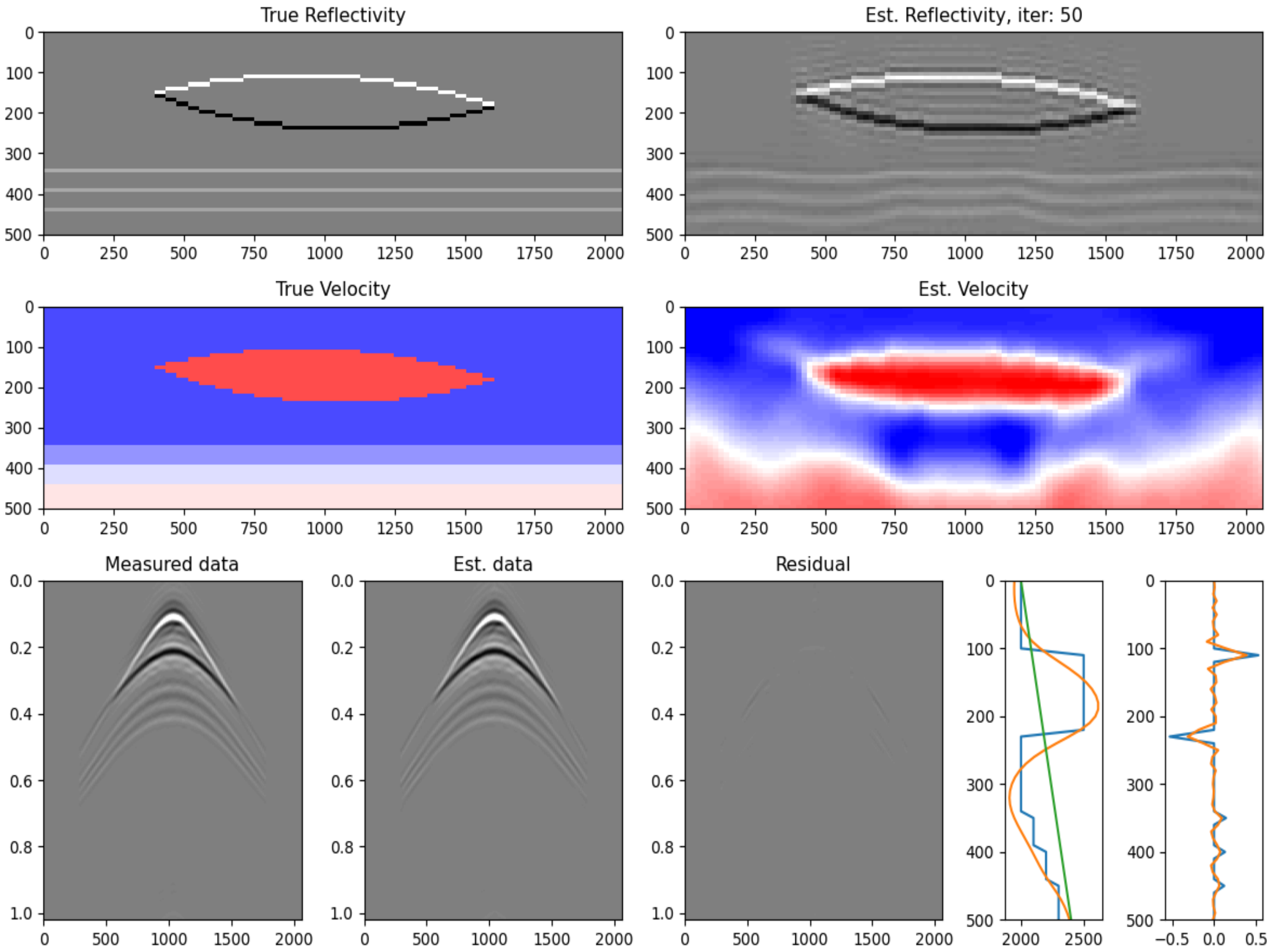




Numerical Experiment for Reflectivity + Velocity Update



Traditional JMI



AI-improved JMI

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Conclusion

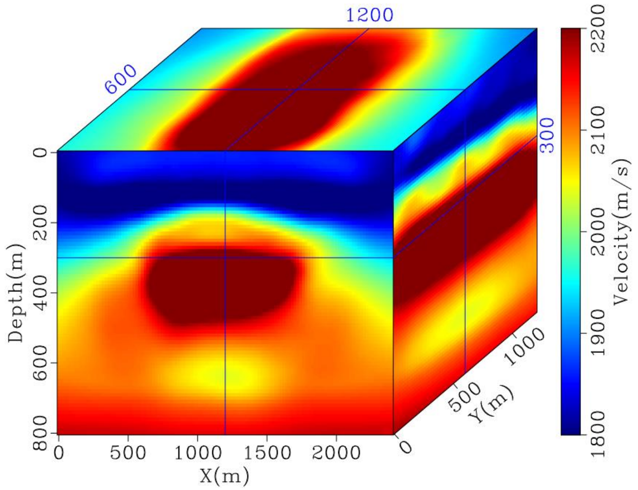
1. We introduced an AI-based interpolation acceleration kernel that uses an Attention U-Net to reconstruct full-band wavefields from sparse frequency inputs, reducing computational costs in FWMod.

2. Demonstrated high reconstruction quality on 2-D models (Lens-shaped, Salt, Marmousi) with low L1 loss and high SSIM / PSNR using 50% of frequencies.

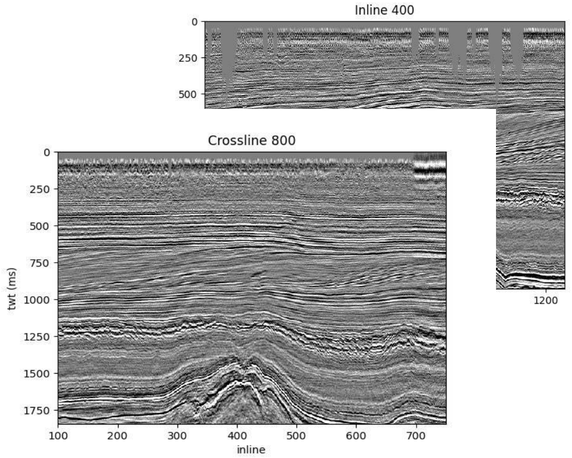
3. Achieved a 1.3 ~ 1.8x speed-up in the reflection-only update stage of JMI by using AI interpolation, with nearly identical convergence compared to full-frequency numerical modeling.

4. With a similar convergence effect, the AI-improved JMI will reduce the time required for the entire process, and is expected to achieve better performance in large-scale 3-D modeling.

Future Works



Extension to 3-D geologies



Validation on field datasets

Integration with HPC techniques

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Delphi Consortium

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Achievements

1. **Zhao J.**, Akram N., Savva N., Verschuur E. An Accelerating Method for 2-D Full Wavefield Modeling Based on Deep Learning, presented at International Workshop on "Computational Modeling of Molecular Systems: From Atoms to the In-silico Design of Materials" , The Cyprus Institute, Cyprus, 20 - 22 May 2024.
2. **Zhao J.**, Akram N., Savva N., Verschuur E. Accelerating 2-D Full Wavefield Forward Modeling via Frequency Interpolation with a Tiny Attention U-Net Based Model, presented at Eighth EAGE High Performance Computing Workshop, KAUST, Saudi Arabia, 16 - 18 September 2024.
3. **Zhao J.**, Akram N., Savva N., Verschuur E. Accelerating 2-D Joint Migration Inversion via Frequency Interpolation in Full Wavefield Migration using Attention U-Net Neural Network, presented at Digitalization in Geoscience Symposium (GEO4.0), Al Khobar, Saudi Arabia, 21 - 24 October 2024.
4. **Zhao J.**, Akram N., Savva N., Verschuur E. AI-Driven Seismic Wavefield Reconstruction via Frequency Interpolation for Efficient Joint Migration Inversion, presented at 86th EAGE Annual Conference & Exhibition, Toulouse, France, 2 - 5 June 2025.

Thank you for listening !

Q & A

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