Mitigating elastic effects of acoustic full waveform inversion for VSP data via deep learning

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Outline

- Motivation
- Method of mitigating elastic effects
- Neural network training results
- Acoustic FWI results
- Time-lapse results
- Conclusions

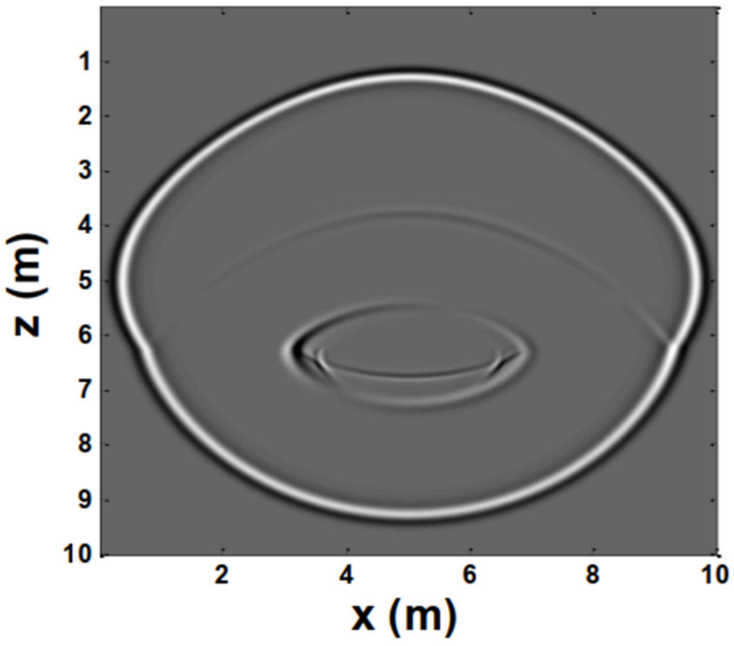
Motivation

Acoustic FWI

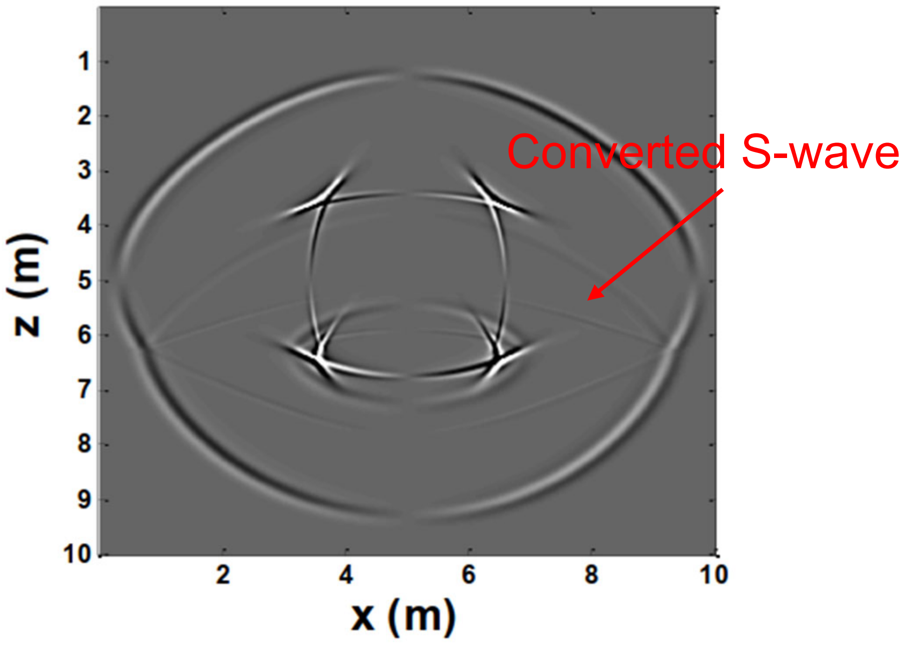
- Efficient and robust
- Less correct due to neglecting elastic effects in the recorded field data

Elastic FWI

- Higher computational costs
- Physically more correct since the observed data do have elastic effects result from PS and SP-wave conversions



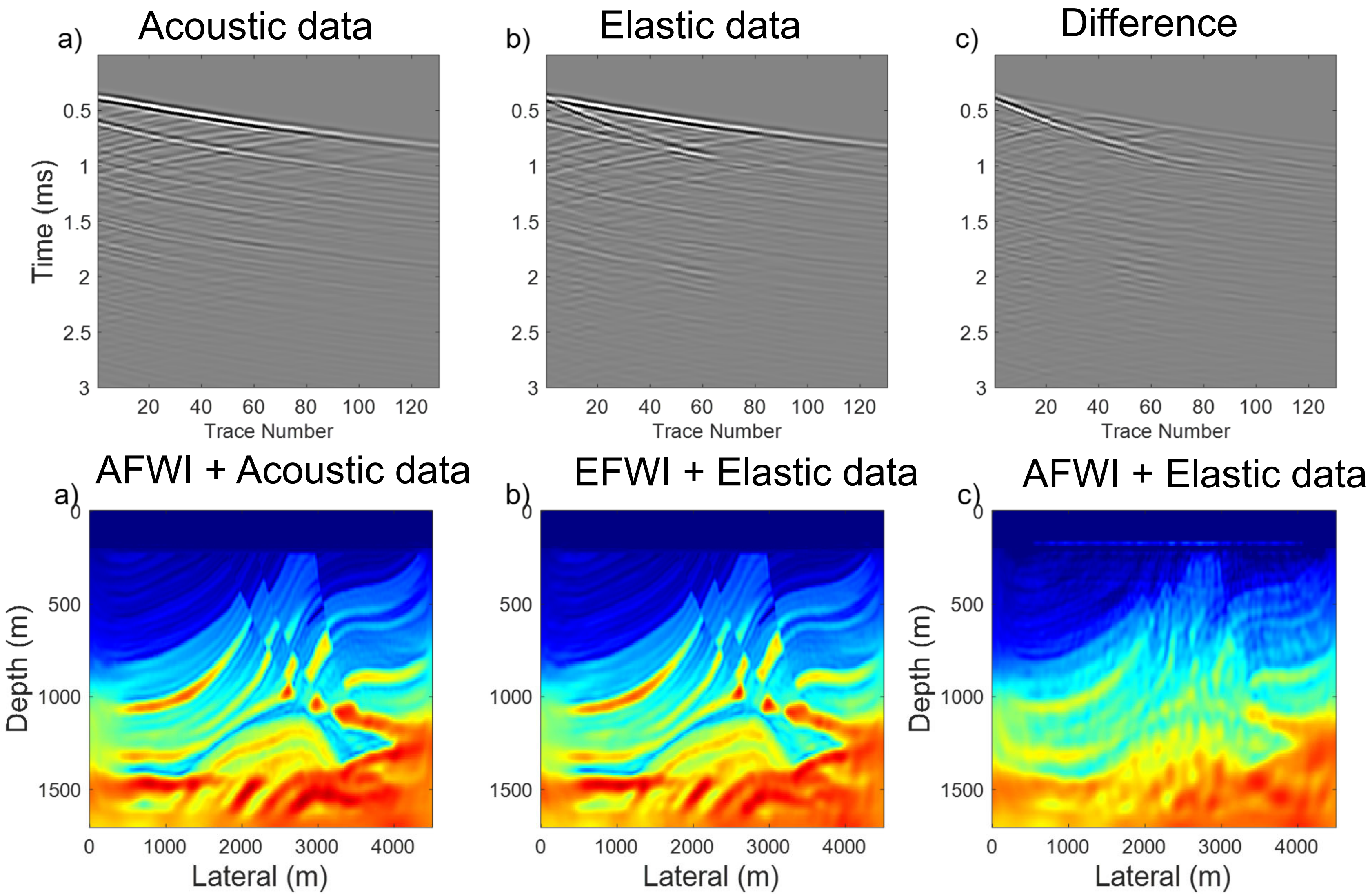
P-wave



P-wave + S-wave

Motivation

Surface survey

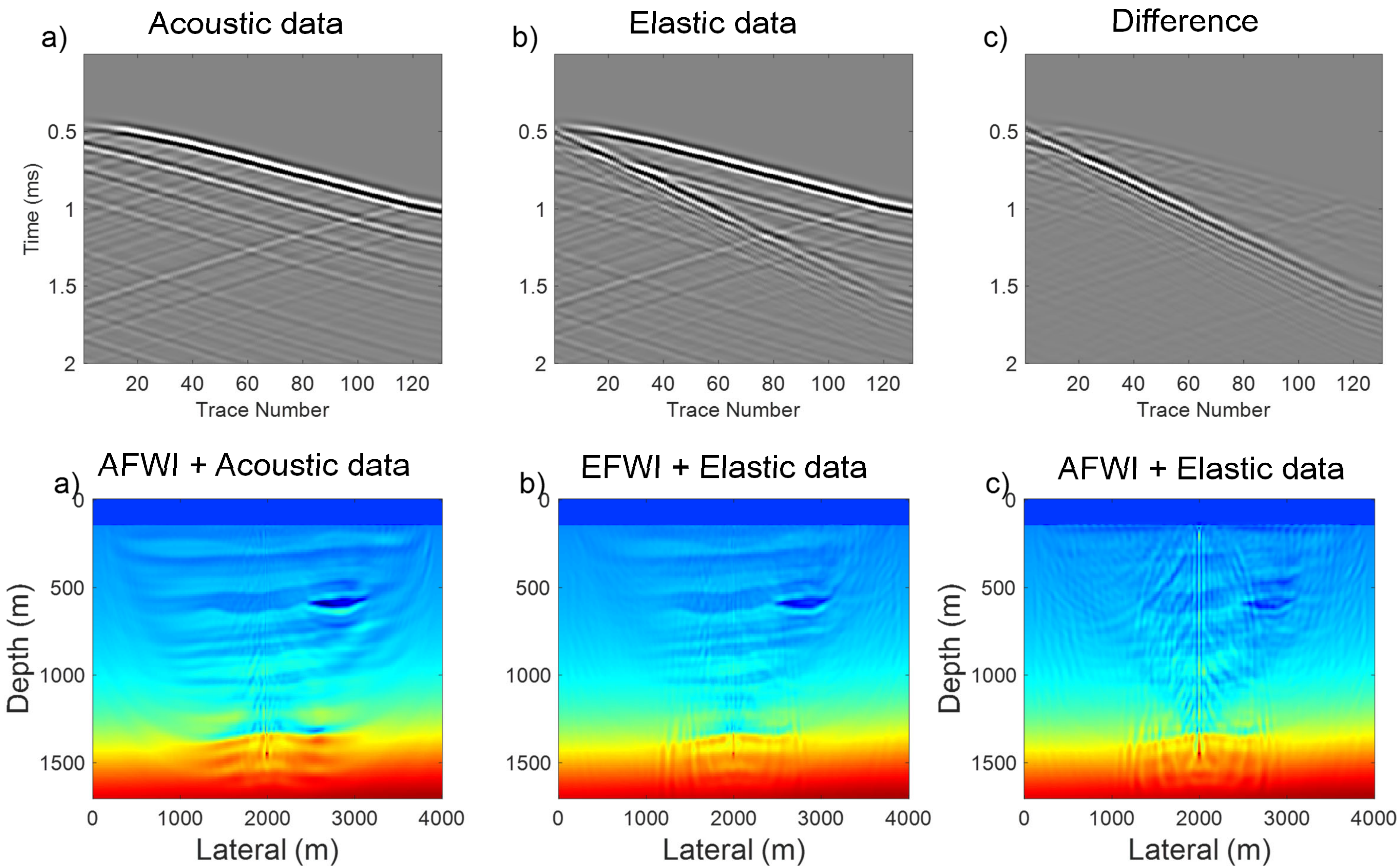


Correction methods:

- acoustic wave equation (Chapman et al., 2014; Hobro et al., 2014)
- elastic data using matching filters (Agudo et al., 2018)
- elastic data using deep learning (Li et al., 2019; Voytan et al., 2022)
- gradient using GANs (Yao t al., 2020)

Motivation

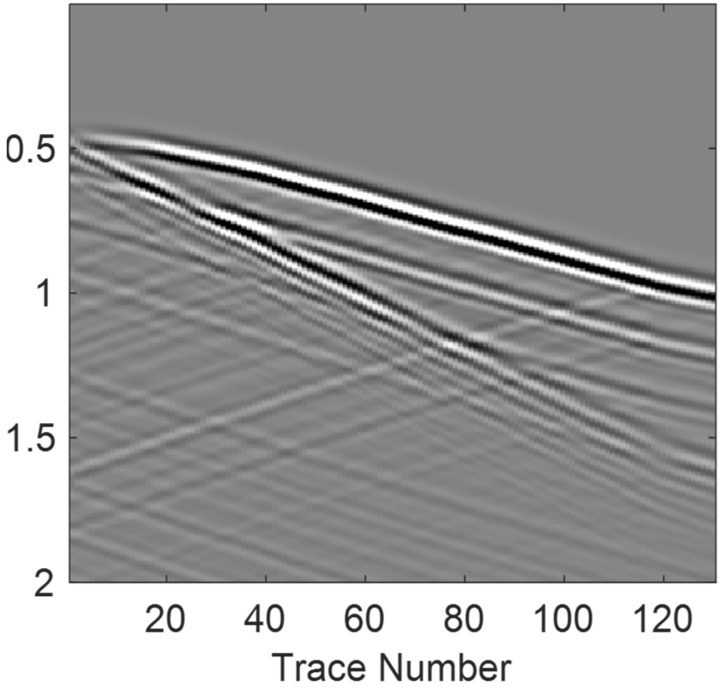
VSP survey



Mitigate the elastic effects in AFWI for VSP data

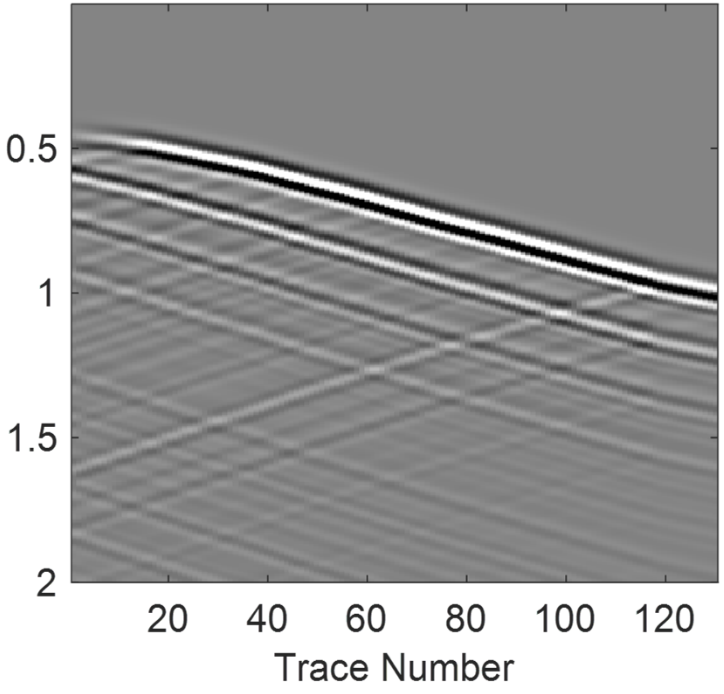
Data domain

Elastic data



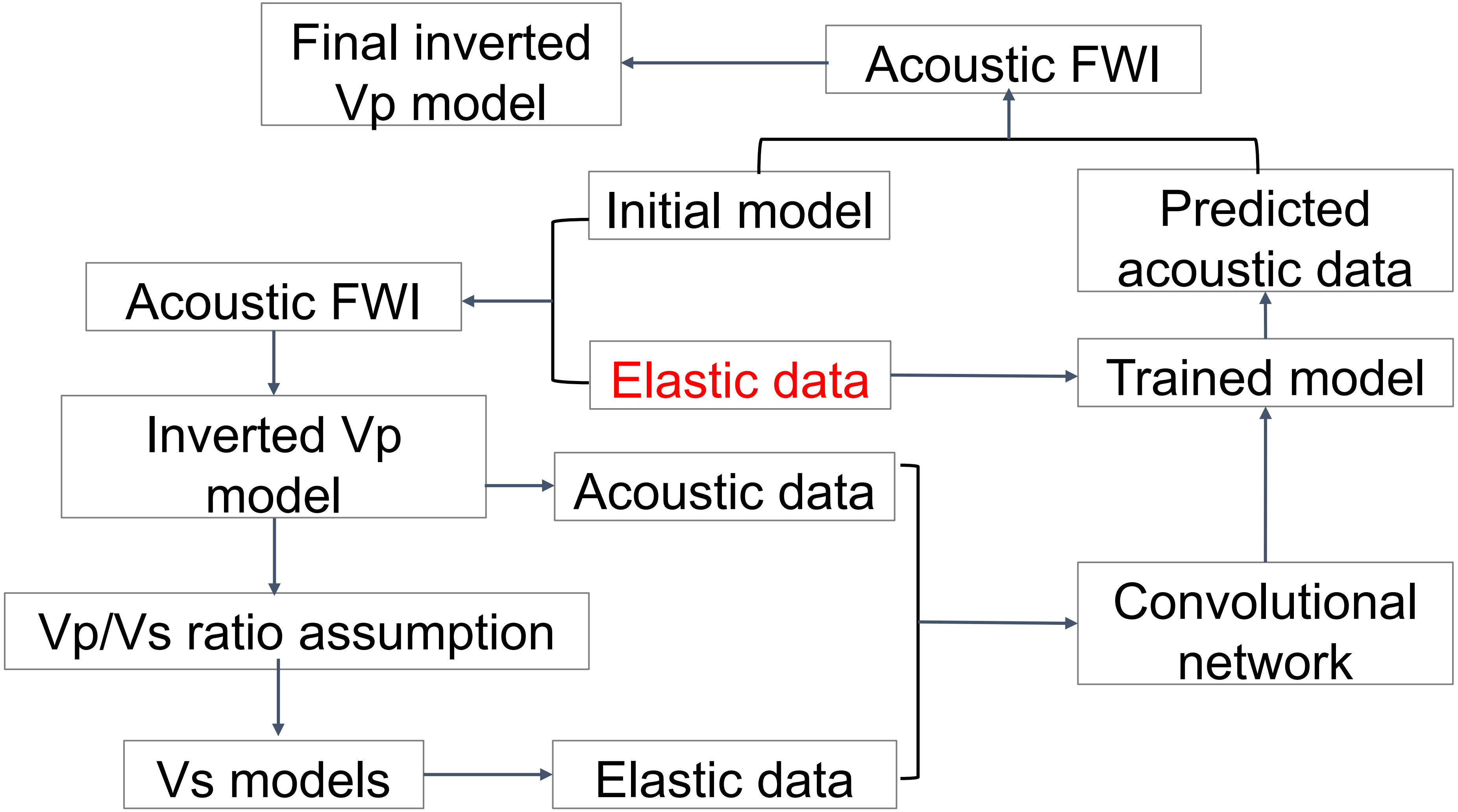
mapping

Acoustic data



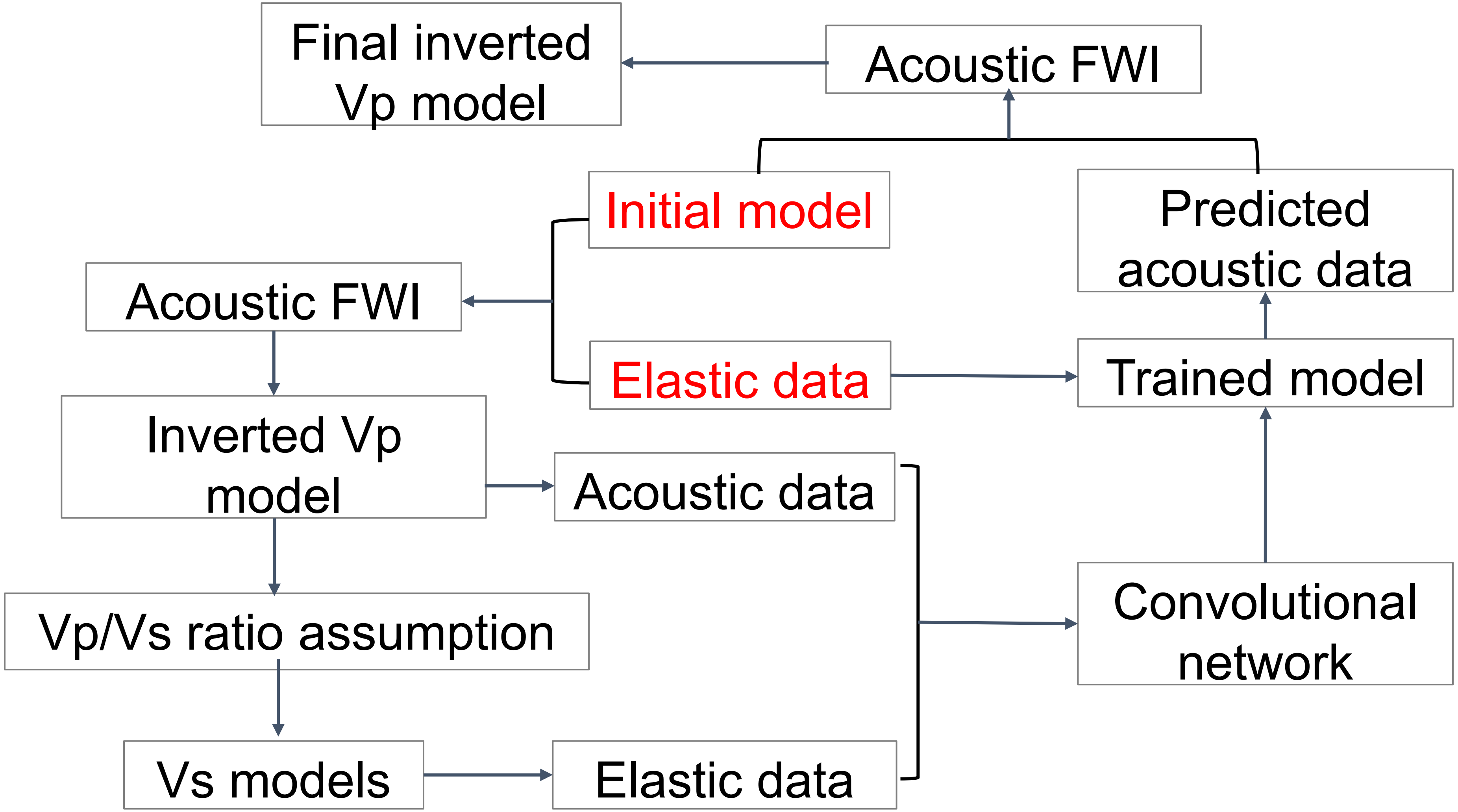
Method

Workflow



Method

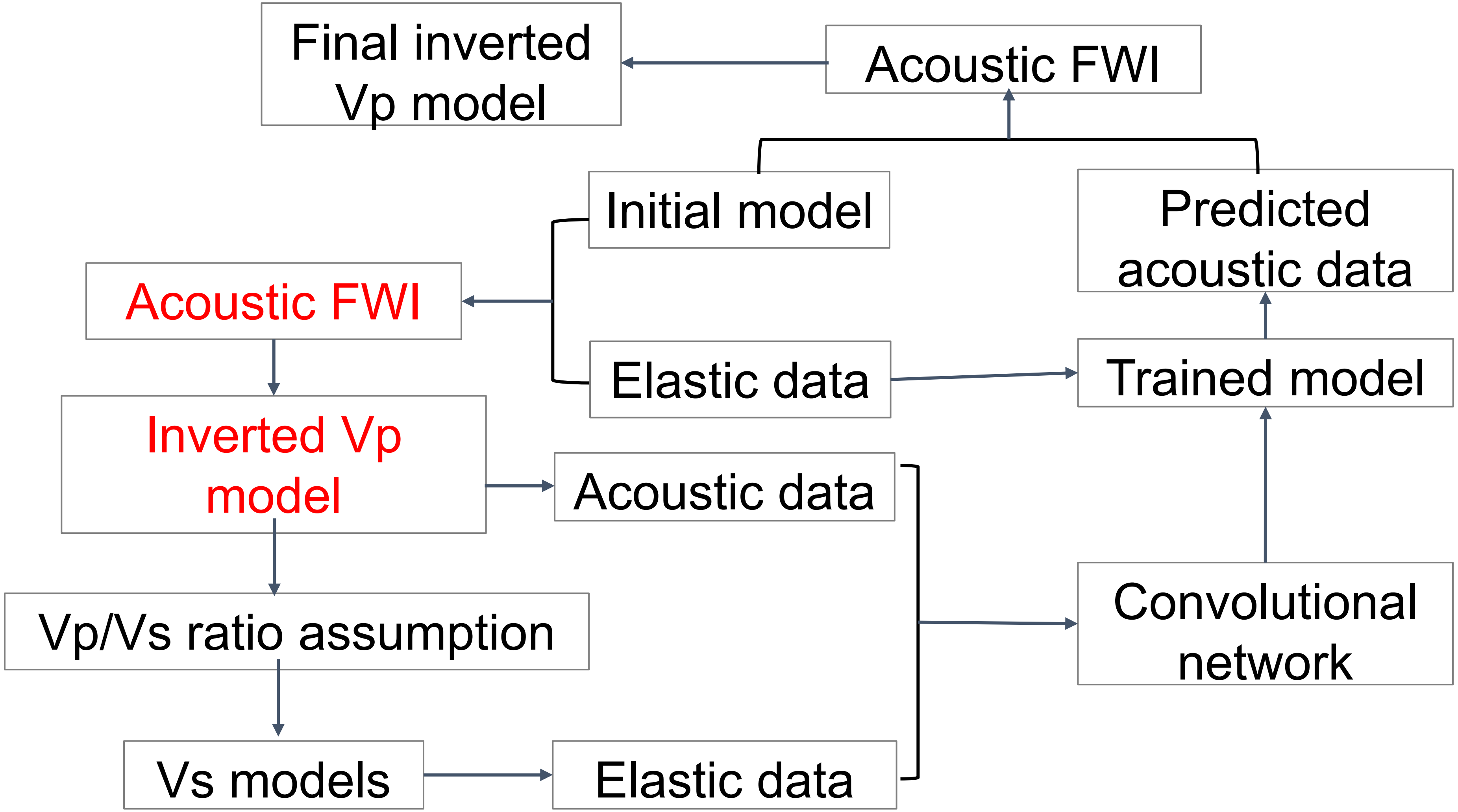
Workflow



Step 1: assume we have access to the initial models necessary for acoustic FWI.

Method

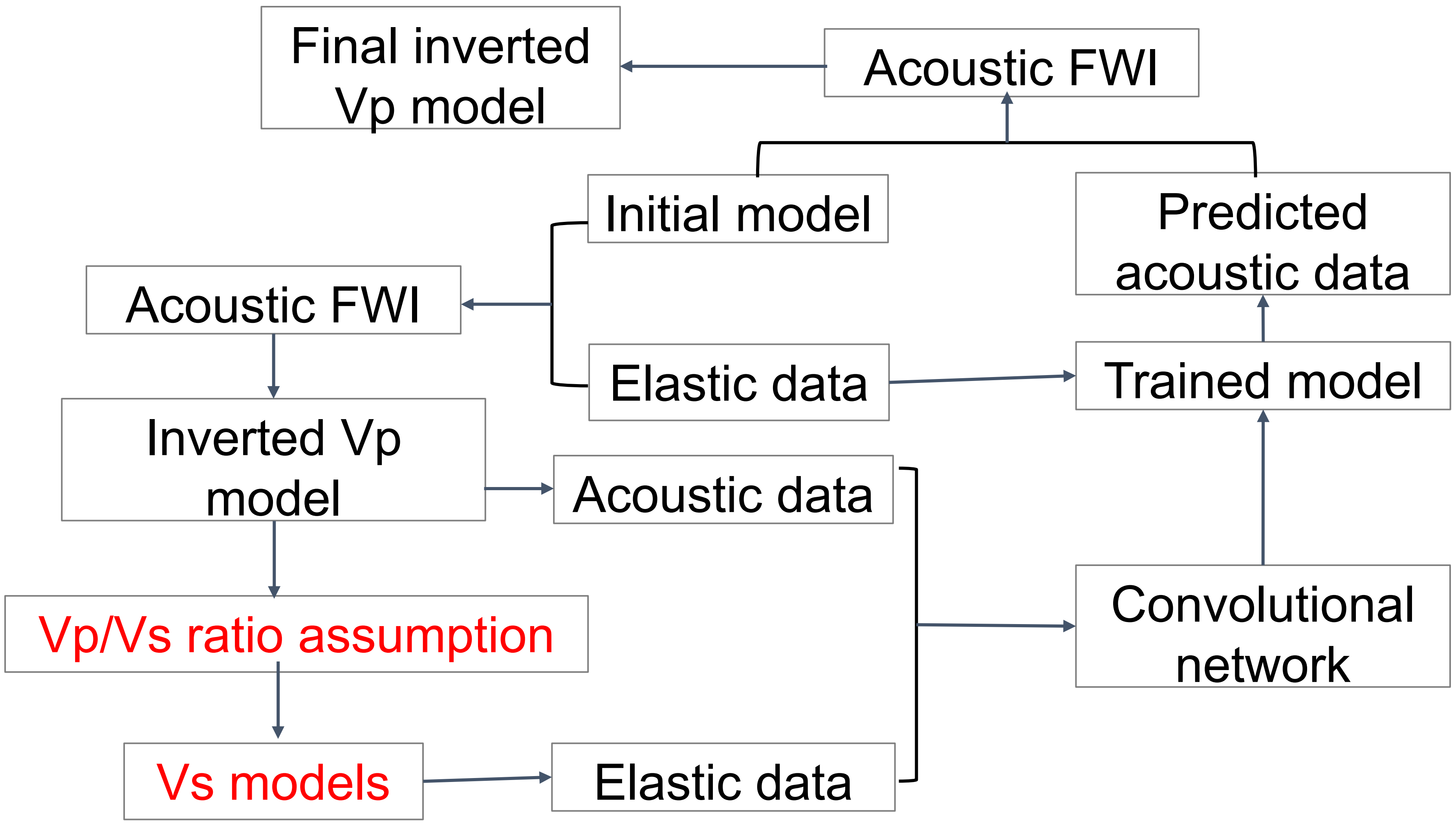
Workflow



Step 2: perform AFWI with initial model to build an acoustic model, which better simulates the field data.

Method

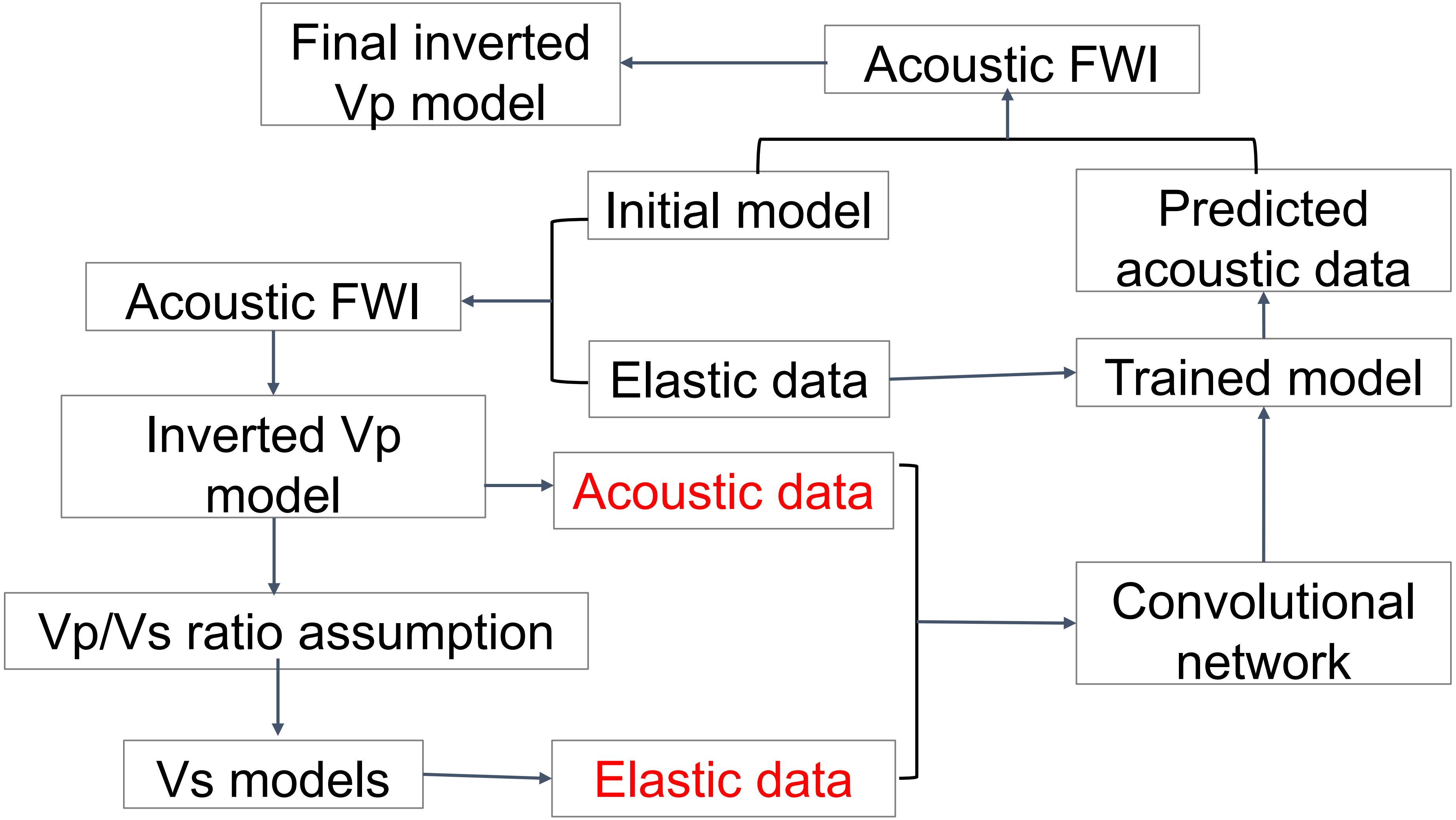
Workflow



Step 3: estimate Vp/Vs ratios to build a series of elastic models.

Method

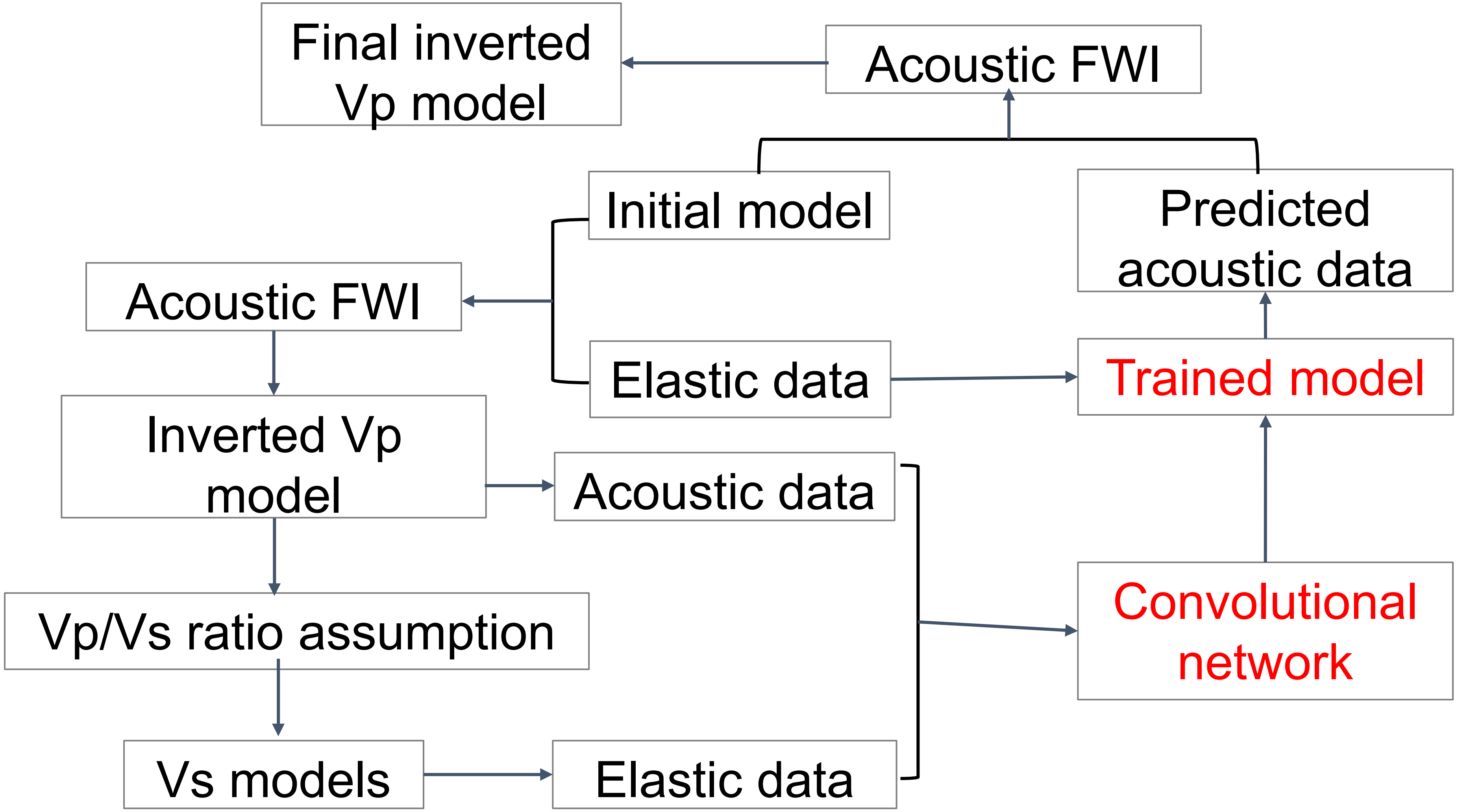
Workflow



Step 4: generate synthetic acoustic and elastic shot gathers using the acoustic and elastic models as the training data.

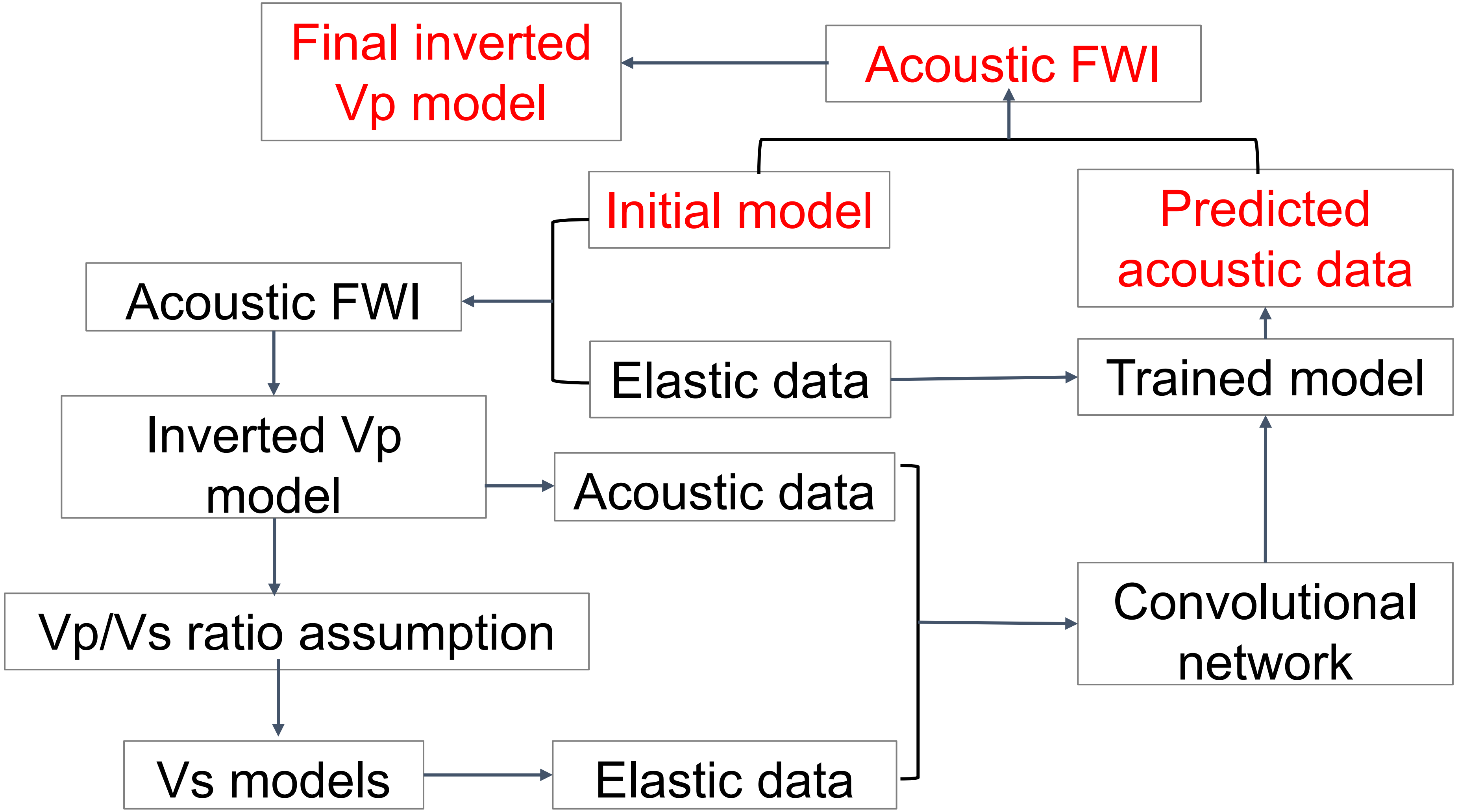
Method

Workflow



Step 5: train the network to learn the mapping from an elastic shot gather to its acoustic equivalent.

Workflow

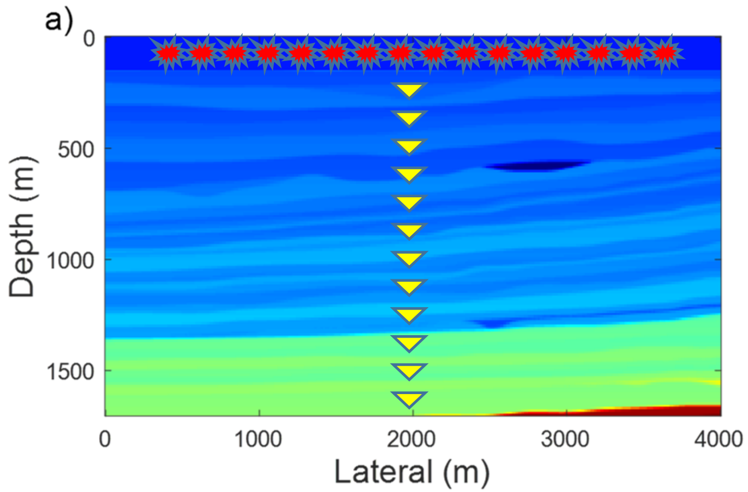


Step 6: apply the network to observed data and perform AFWI.

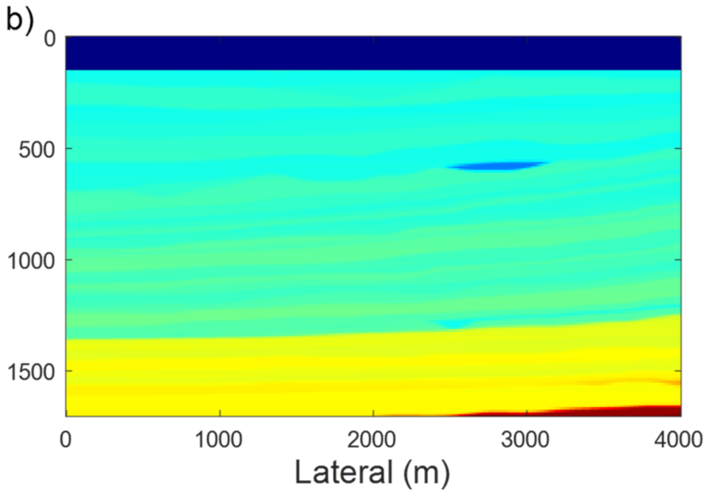
Result

Model and geometry

True Vp

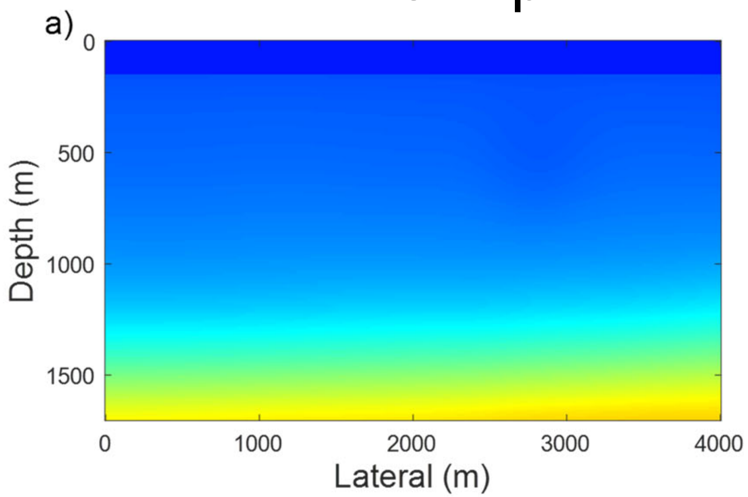


True Vs

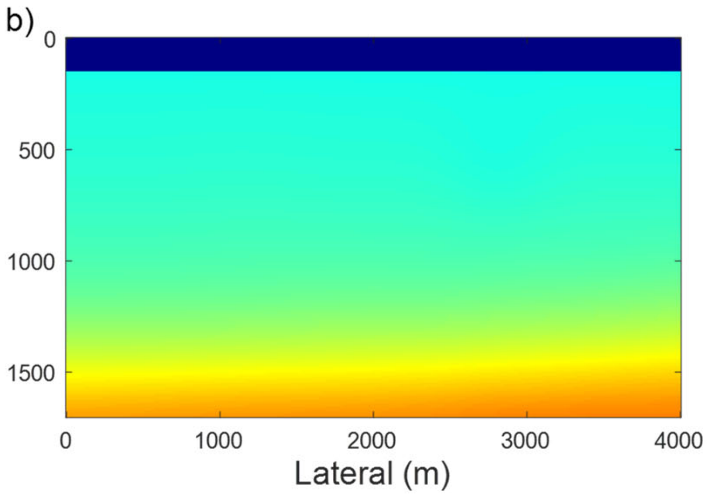


36 sources
128 receivers

Initial Vp



Initial Vs



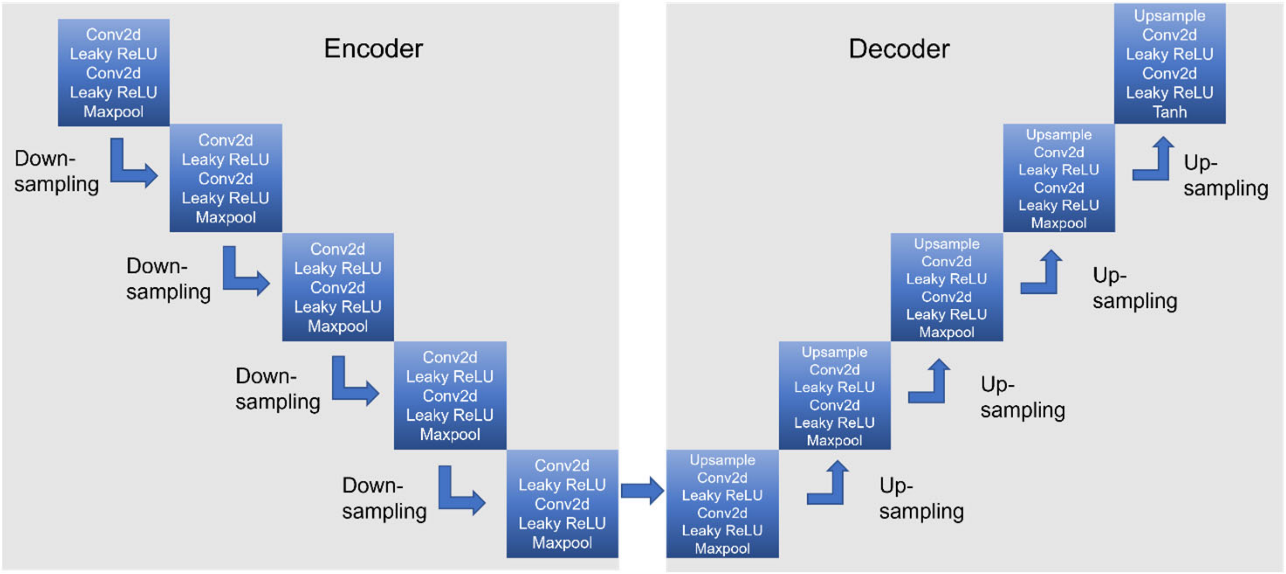
Data preparation and training

Data preparation

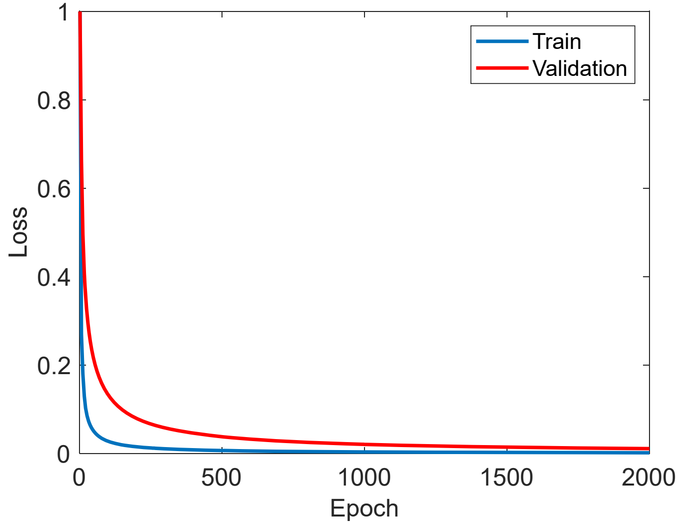
- Generate 1800 acoustic and elastic shot gather pairs.
- Training data: 2880
- Validation data: 360
- Test data: 360

Training

Optimizer	ADAM
Software	PyTorch
Hardware	NVIDIA A100
Training time	~8 hours
Learning rate	0.0001
Loss function	MSE
Batch size	50



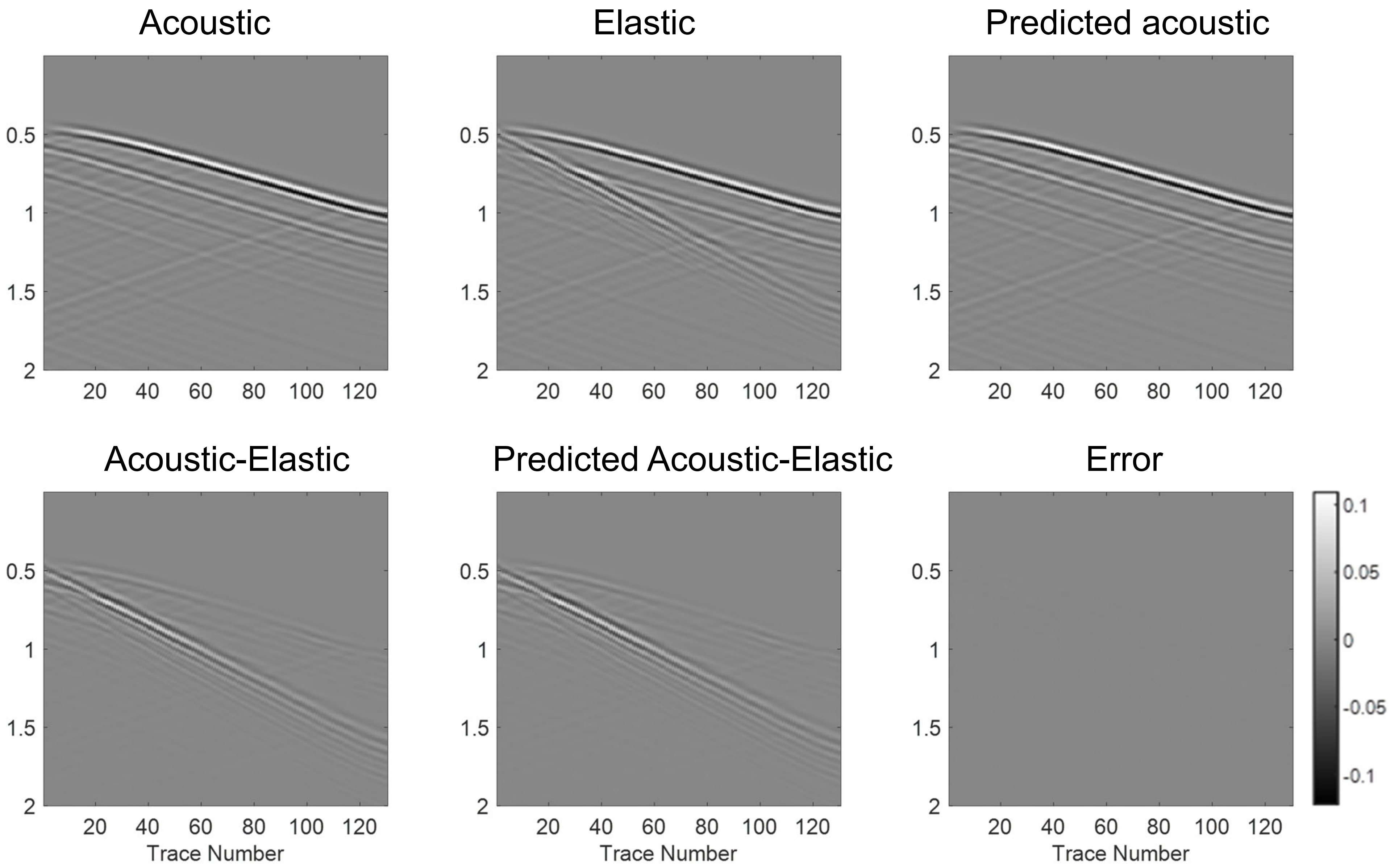
Architecture of the convolutional neural network



Loss

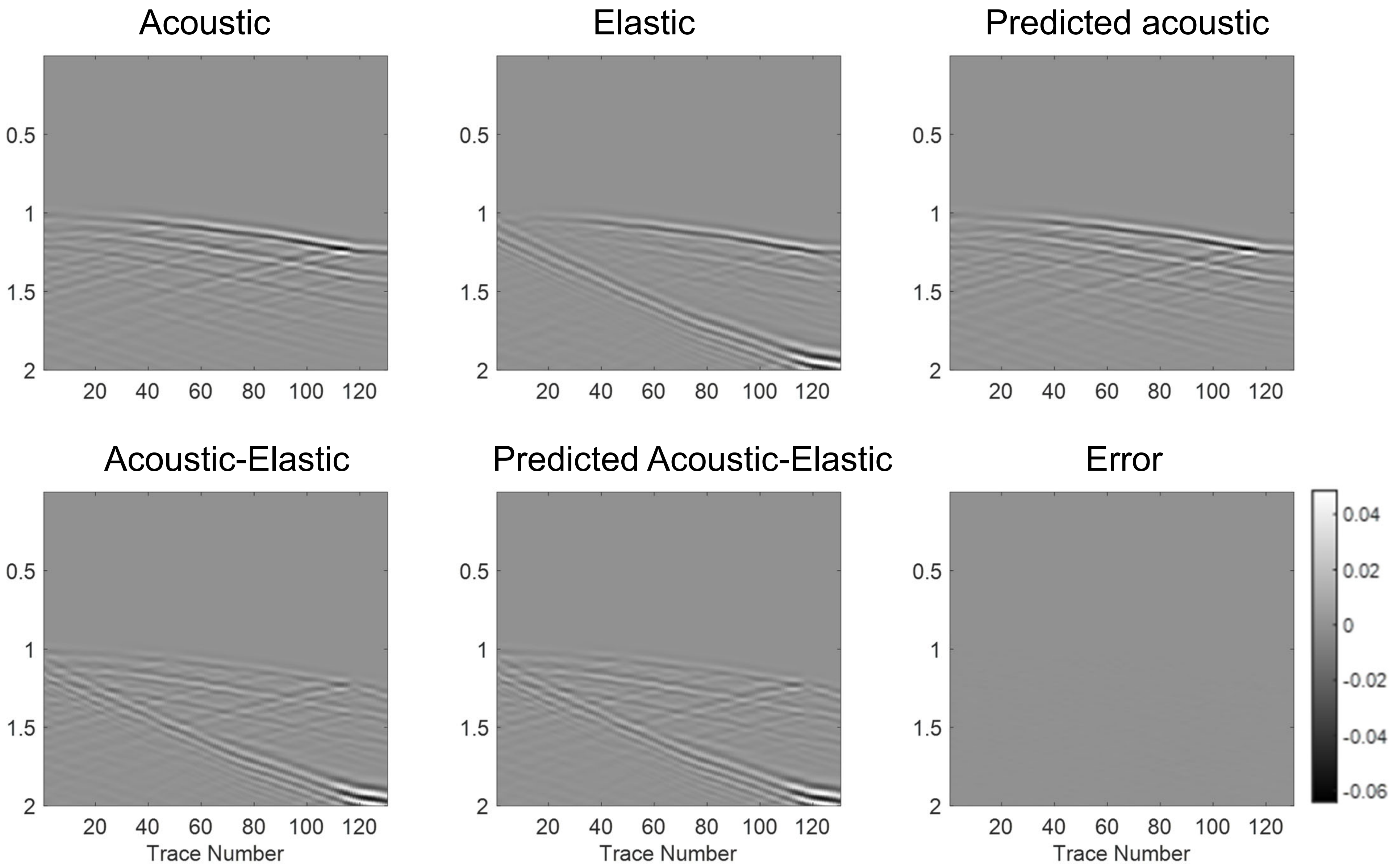
Predicted test data

Near offset



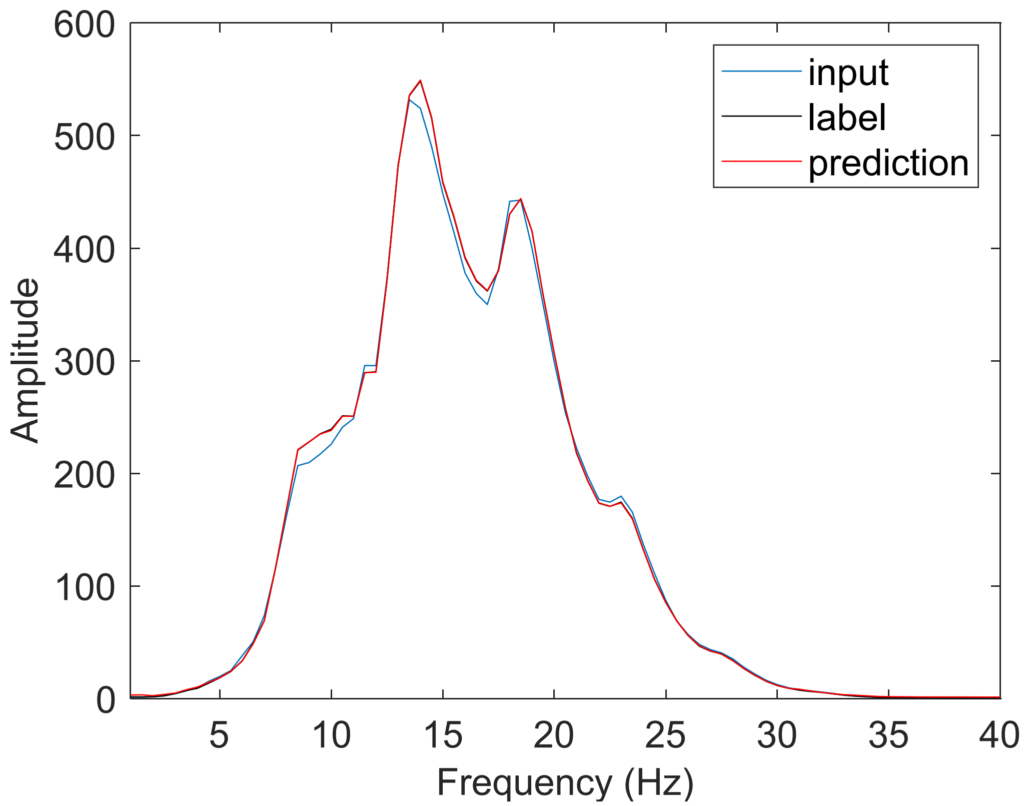
Predicted test data

Far offset

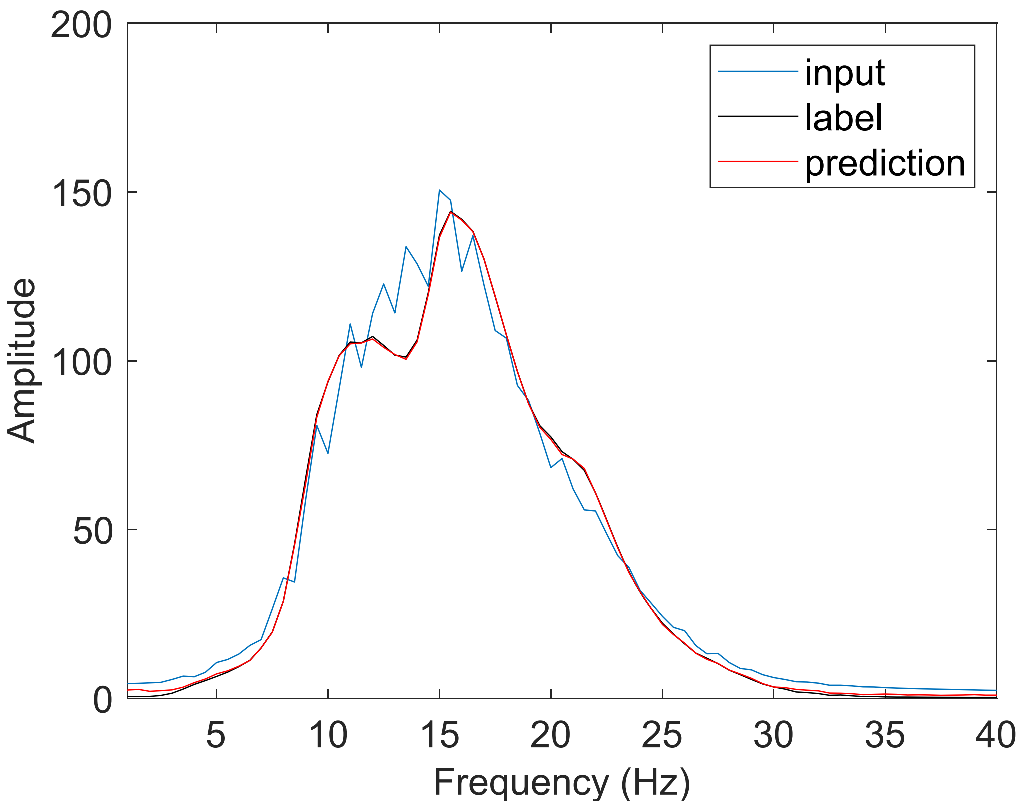


Spectra comparison

Spectra comparison



Near offset

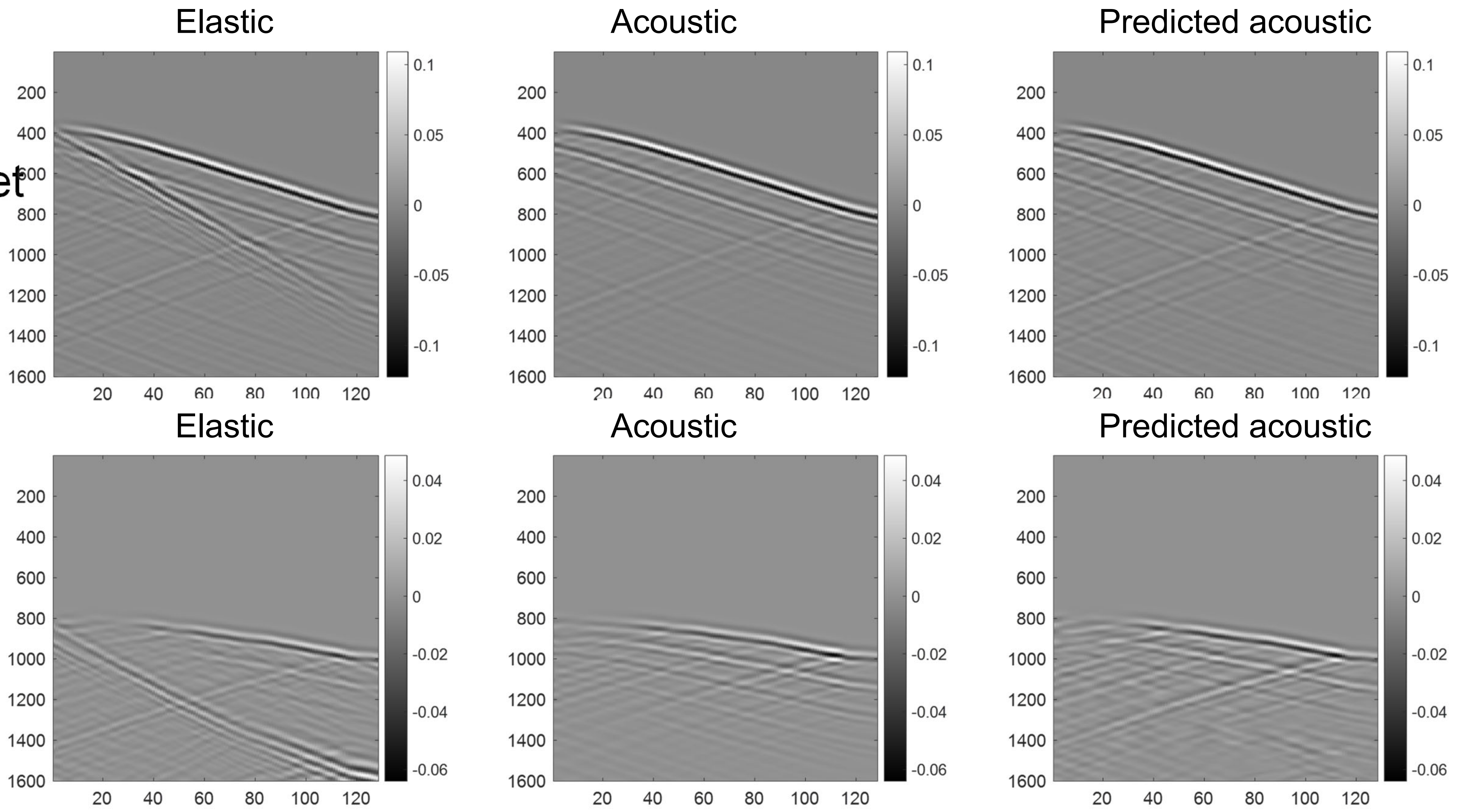


Far offset

Predicted observed data

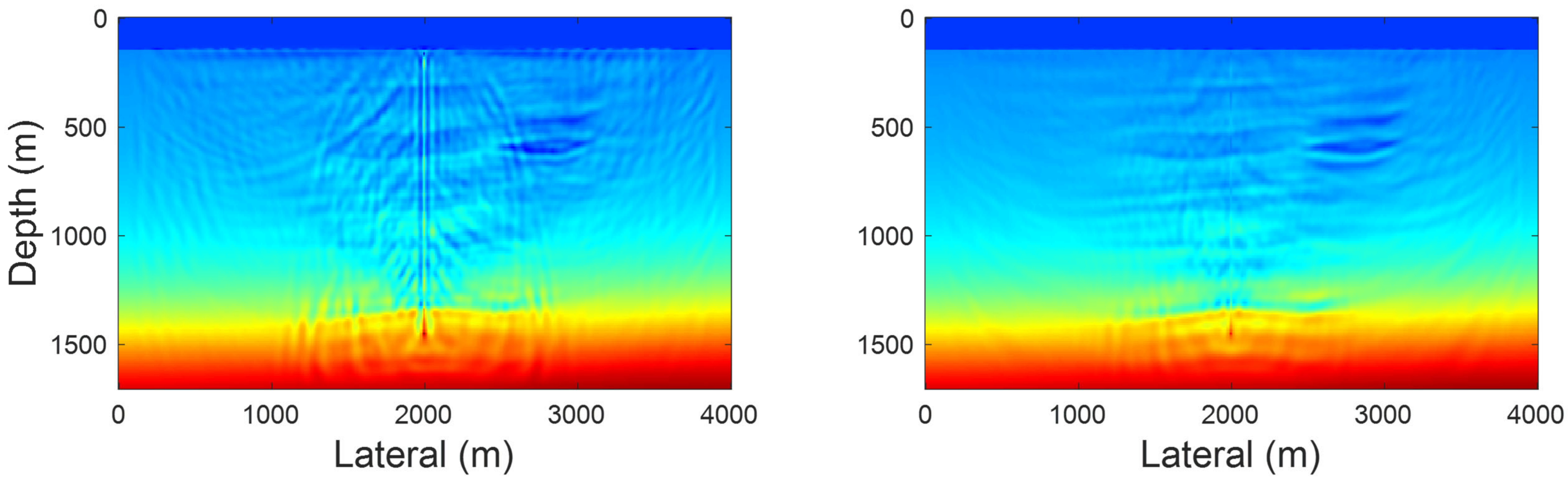
Near offset

Far offset



Baseline inversion result

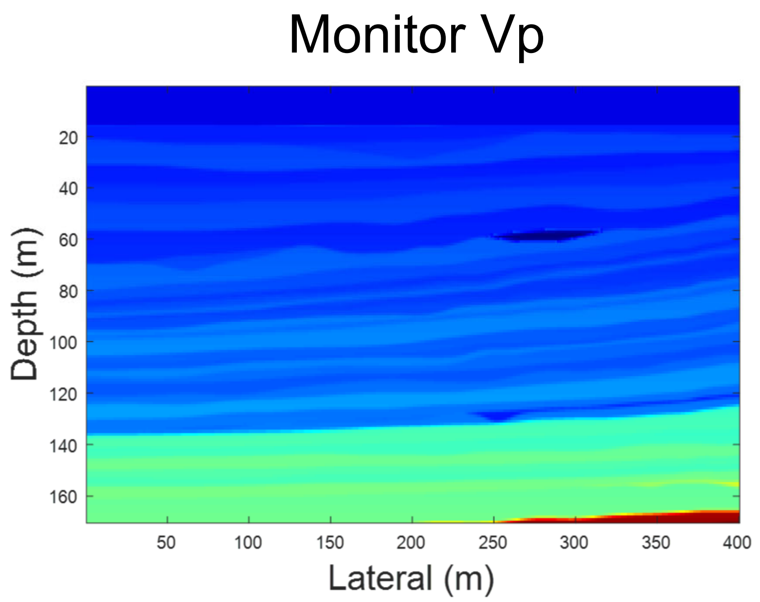
AFWI results

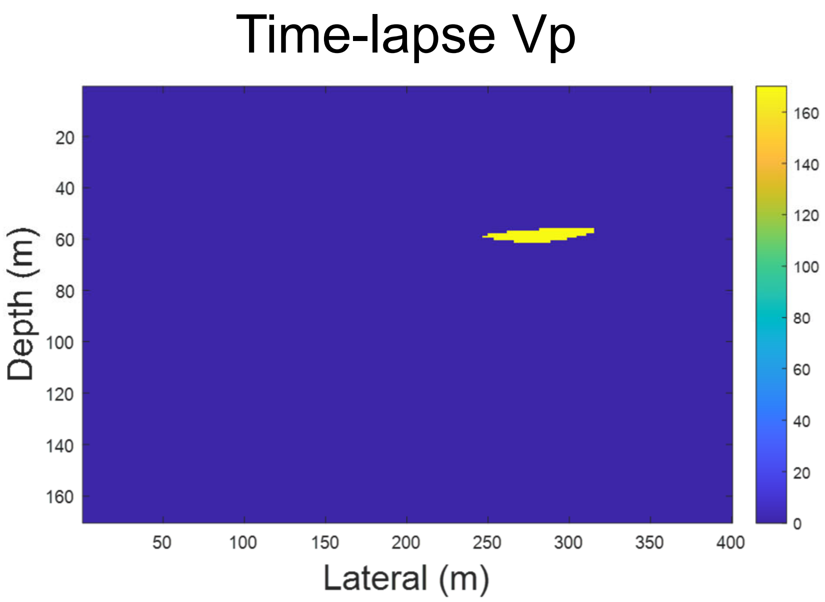


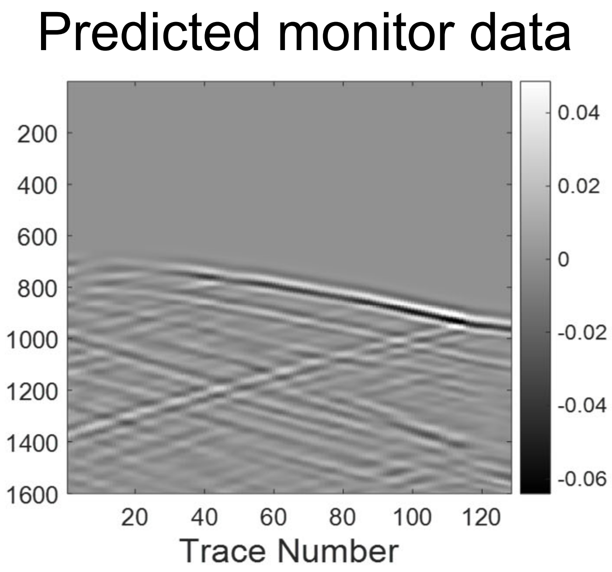
AFWI + Elastic data

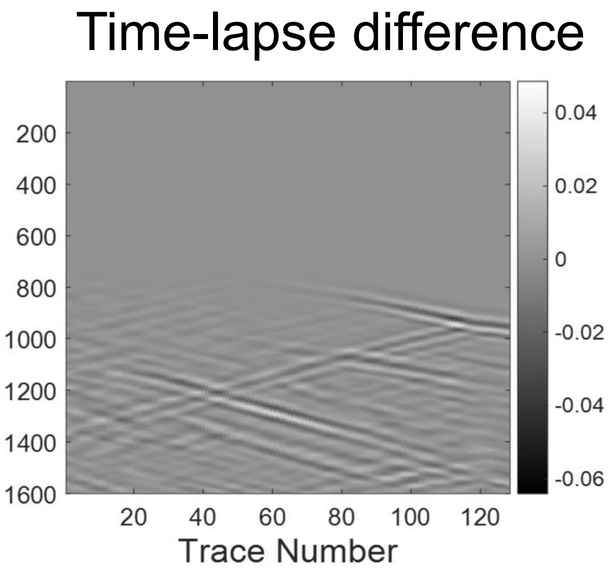
AFWI + predicted acoustic data

Time-lapse inversion results

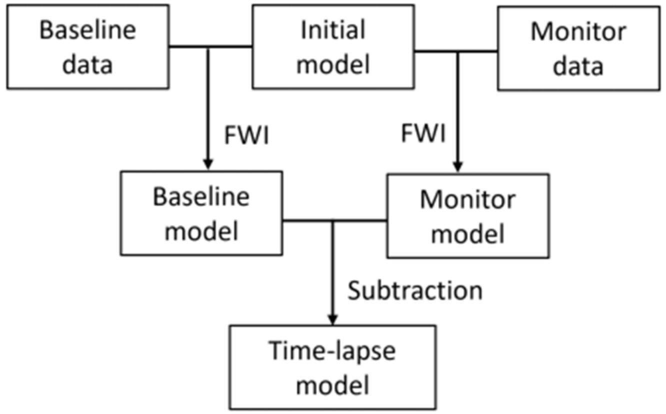


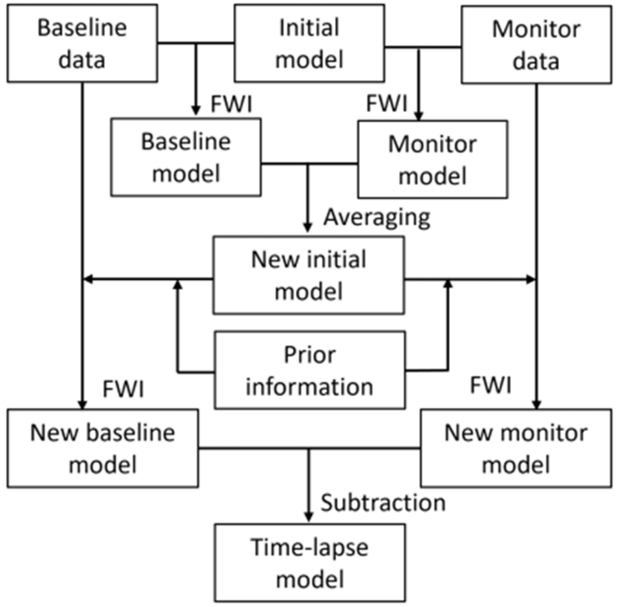






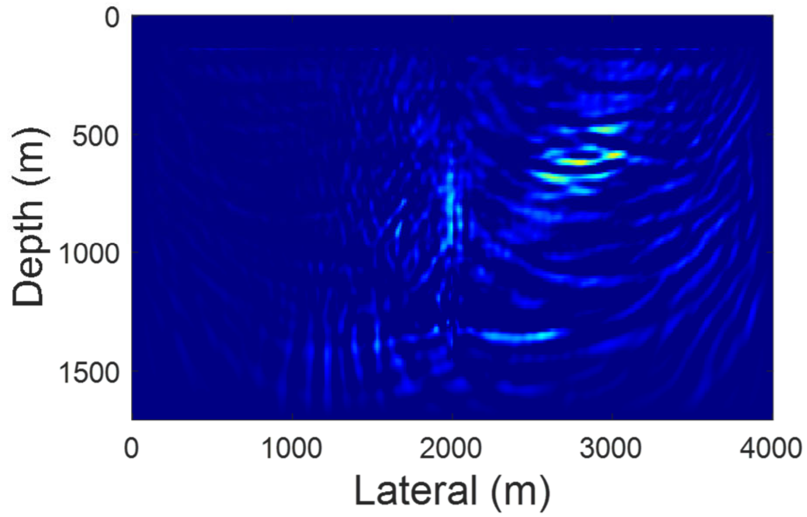
Time-lapse inversion results

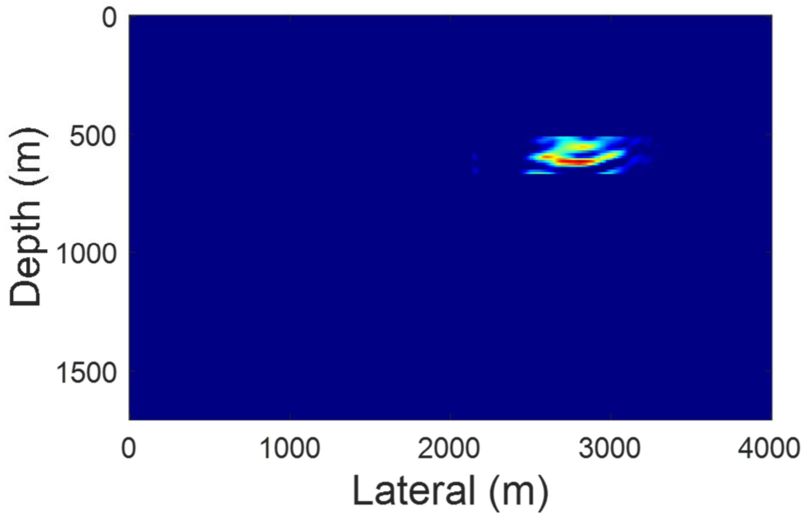




Parallel strategy

Target-oriented common model strategy



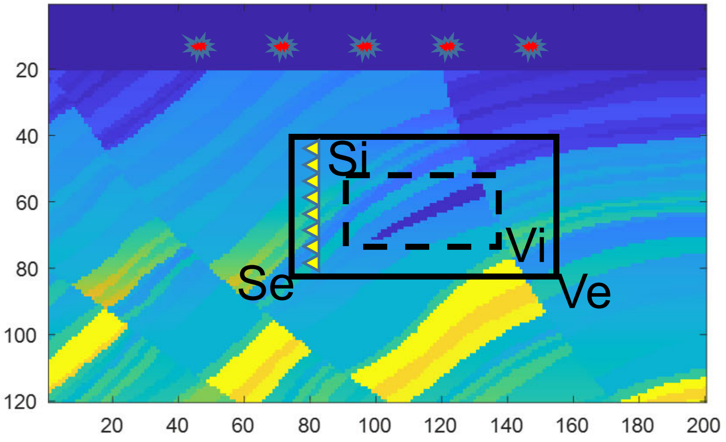


Conclusions

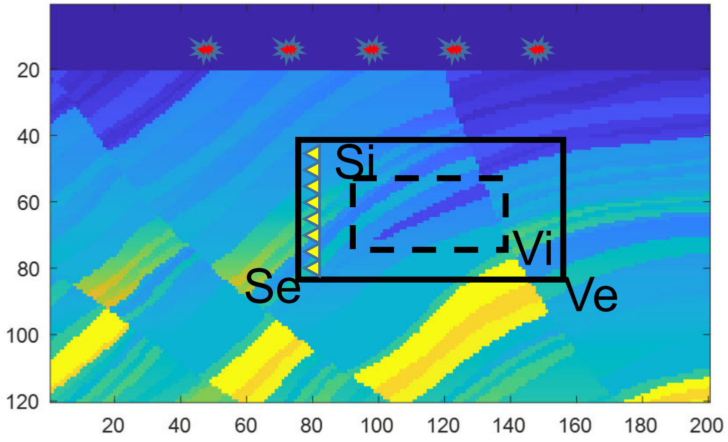
- We develop a deep convolutional network to correct VSP seismic data to mitigate elastic artifacts in acoustic FWI.
- Predicted data show that elastic wave phenomena can be effectively mitigated by the deep learning approach.
- The image quality of inverted model by acoustic FWI can be improved after the elastic data are transformed into their acoustic counterparts.
- We have conducted time-lapse acoustic FWI using acoustic baseline and monitor data predicted by this deep learning approach, the inversion results show this approach can be applied into monitoring velocity changes.
- This approach can decrease the computational cost and improve the monitoring efficiency.

Future work

Incorporate a local solver like the FD-injection method (Robertsson and Chapman, 2000)

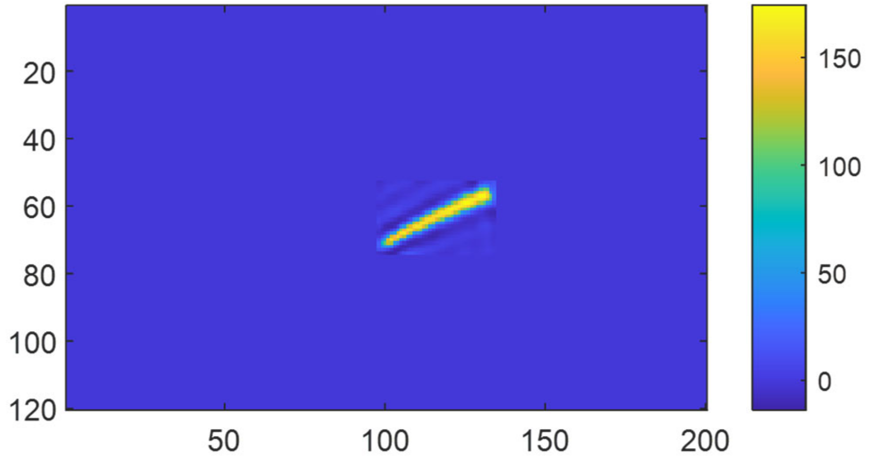


Baseline model



Monitor model

- Si and Vi are the injection surface and subvolume.
- Ve is an FD submesh for the second simulation and Se acts like an AB.



Time-lapse result

- Based on the baseline model, calculate the wavefields at certain surface as effective sources.
- Chose receivers lies in the area and use the baseline and monitor data difference as observed data.

Acknowledgements

- CREWES sponsors, staff and students
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