

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

He Liu, Luping Qu, Daniel Trad and Kris Innanen
he.liu1@ucalgary.ca

Abstract

Acoustic full waveform inversion is usually the first choice for velocity model building due to its efficiency and robustness. However the recorded field data always contain elastic effects due to such as PS and SP-wave conversions. In this work, we adopt a deep learning approach to mitigate the elastic effects in VSP data. We train convolutional network to map elastic shot gathers into their acoustic counterparts, and perform acoustic FWI using the pseudo-acoustic shot gathers. Our experiments show that the transformed acoustic data can match well with the direct simulated acoustic data. And the inversion results also show improvement compared with the inversion result by acoustic FWI using elastic data.

Introduction

Despite the elastic nature of the earth, the wavefield is usually assumed acoustic and the acoustic wave equation is typically used to model wave propagation in FWI. This assumption is essential for being efficient, especially conducting FWI for frequent time-lapse monitoring surveys or large scale 3D datasets (Agulo, et al., 2018; Li et al. 2019; Voytan et al. 2022). In Fig 1, we compare the acoustic shot gather and the elastic shot gather simulated using models with the same structure. In Fig 1c, we can notice the difference results from the elastic effects. In Fig 2, we compare the FWI results in three scenarios, acoustic FWI using acoustic data, elastic FWI using elastic data and direct acoustic FWI using elastic data. We can notice the artifacts introduced by elastic effects. In this work, we adopt a deep learning approach to mitigate the elastic effects in VSP data.

Methods

Following Li et al. (2019) and Voytan et al. (2022), we train a deep convolutional network (CNN) to learn a data driven mapping between shot gathers generated in an elastic model and shot gathers in an acoustic model. The workflow is shown in Fig 3. First, we assume that we have access to observed data acquired at the surface and the initial Vp model as is necessary for acoustic FWI. then we invert Vp for a few iterations of acoustic FWI from the initial model. In this way, we can obtain an acoustic model, which will be used to simulate field data as well as build an elastic model through an assumption of Vp/Vs ratio. This estimate is based on out initial Vs model and allows for variability between subsurface structures.

After building the elastic models, we use them and the acoustic model to generate synthetic acoustic and elastic shot gather pairs under the same acquisition geometry. Then we use the data pairs to train a deep convolutional network to learn the mapping from an elastic shot gather to an acoustic equivalent. At last, we apply the trained network to elastic observed data to perform acoustic FWI.

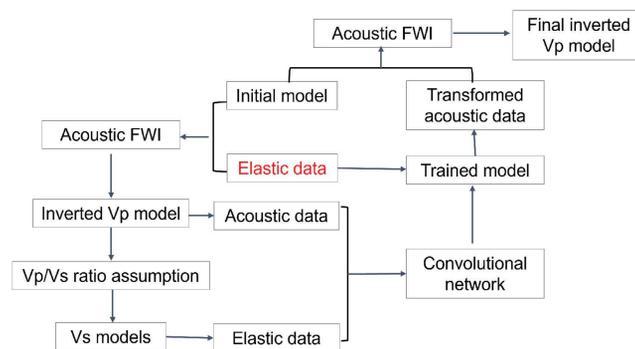


Figure 3: Workflow.

Results

In Fig 4 and Fig 5, we present the true and initial models.

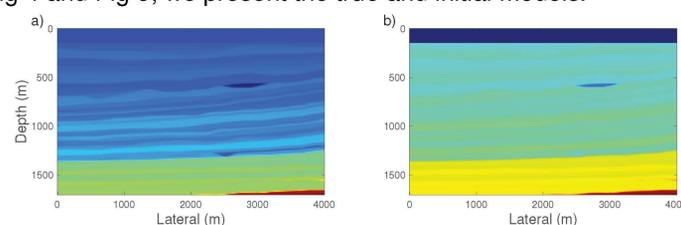


Figure 4: The true model, a) Vp model, b) model.

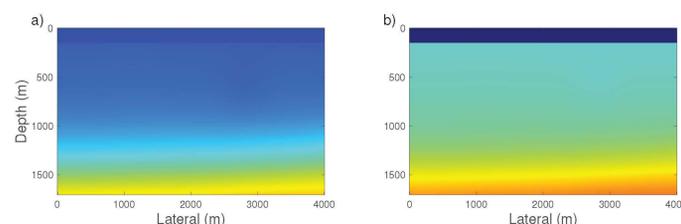


Figure 5: The initial model, a) Vp model, b) model.

In Fig 6, we can notice the predicted acoustic shot gather can match well with direct simulated acoustic shot gather. Then we use this network to predict the acoustic counterparts of observed elastic shot gathers and perform acoustic FWI, the inversion result is shown in Fig 7, compared with Fig 2c, we can notice FWI result using this deep learning approach has been improved.

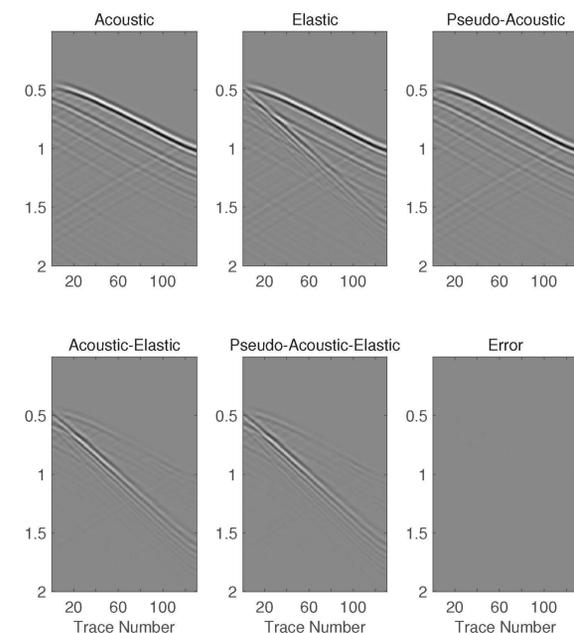


Figure 6: Shot gathers, a) acoustic, b) elastic, c) transformed acoustic, d) difference between acoustic and elastic, e) difference between transformed acoustic and elastic, e) difference between acoustic and transformed acoustic.

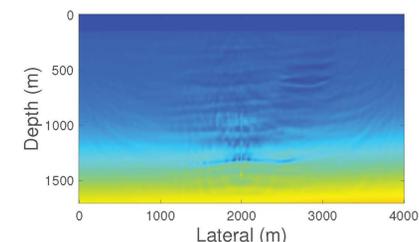


Figure 7: Acoustic FWI result using transformed acoustic data.

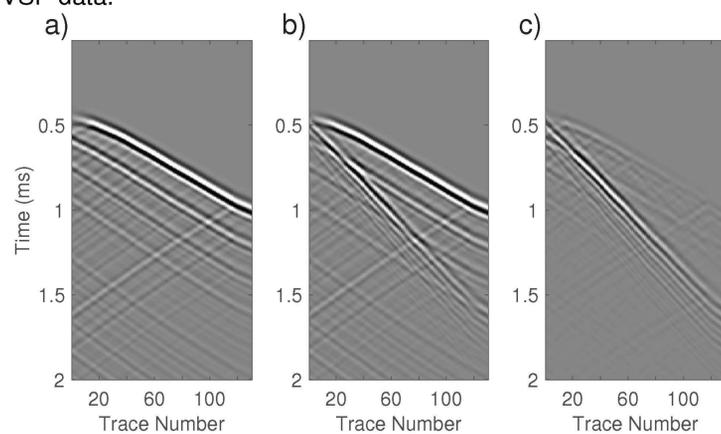


Figure 1: a) Acoustic shot gather, b) Elastic shot gather and c) The difference.

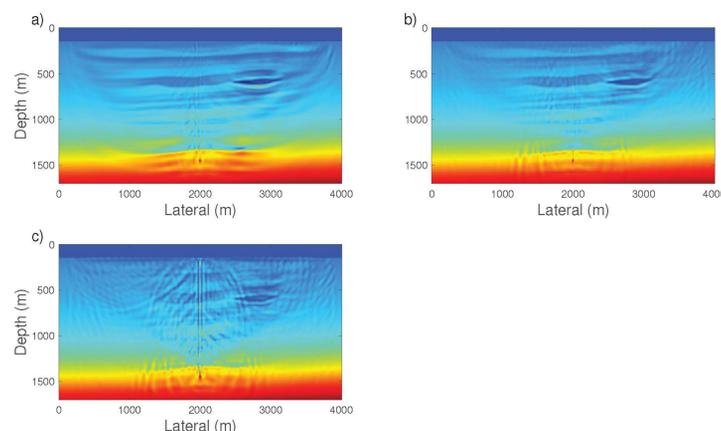


Figure 2: FWI results: a) acoustic FWI using acoustic data, b) elastic FWI using elastic data, c) acoustic FWI using elastic data.

Conclusions

We develop a deep convolutional network to correct VSP seismic data to mitigate elastic artifacts in acoustic full waveform inversion of geophone VSP data. In this work, we implemented and tested a deep-learning approach of using convolutional neural networks to reduce elastic effects in observed VSP data for acoustic FWI. Our synthetic tests show that elastic wave phenomena can be effectively suppressed by the deep learning approach and the models from acoustic FWI were significantly improved by using the transformed elastic dataset.

Acknowledgement

The sponsors of CREWES are gratefully thanked for continued support. This work was funded by CREWES industrial sponsors, NSERC (Natural Science and Engineering Research Council of Canada) through the grant CRDPJ 543578-19.

References

- Voytan D, et al. Mitigating elastic effects of acoustic full-waveform inversion with deep learning and application to field data[C]//SEG International Exposition and Annual Meeting. SEG, 2022.
- Li D, et al. A deep learning approach for acoustic FWI with elastic data[C]//SEG International Exposition and Annual Meeting. SEG, 2019.