Geologic stratigraphic scenario testing via deep learning towards imaging beyond seismic resolution

Karimzadanzabi, A.; Cuesta Cano, A.; Verschuur, E.

DOI
10.3997/2214-4609.2023101151

Publication date
2023

Document Version
Final published version

Citation (APA)
Karimzadanzabi, A., Cuesta Cano, A., & Verschuur, E. (2023). *Geologic stratigraphic scenario testing via deep learning: towards imaging beyond seismic resolution*. Paper presented at 84th EAGE ANNUAL Conference and Exhibition 2023, Vienna, Austria. https://doi.org/10.3997/2214-4609.2023101151

Geologic stratigraphic scenario testing via deep learning: towards imaging beyond seismic resolution

A. Karimzadanzabi[1], A. Cuesta Cano[1], E.J. Verschuur[1]

[1] TU Delft

Summary

In the process of seismic subsurface imaging, there is no acceptable forward model reflecting the AVO response in a laterally inhomogeneous medium for reservoir characterization. This means that even when inversion is performed in full waveform, local heterogeneity is typically not fully incorporated while emplying a local 1.5D assumption. Thus, it is impossible to image and classify the subsurface features with these local heterogeneities. Still, the angle-dependent response encodes heterogeneity information that assists overcoming this issue if used properly. To exploit its capabilities, we present a way for identifying reservoir characteristics in the presence of local heterogeneity by linking encoded angle-dependent responses created using angle-dependent Full Wavefield Migration with their originating source - the relevant geological context. To accomplish this purpose, a pipeline technique that integrates the produced angle-dependent responses with a pattern categorization deep-learning tool is proposed. For a basic test on synthetic data, the method successfully identified the produced different stratigraphic architectures and classified them in the training stage. The method is then validated on angle gathers generated from different models with comparable geological circumstances.

Geologic stratigraphic scenario testing via deep learning: towards imaging beyond seismic resolution

Introduction

In the process of seismic subsurface imaging and characterization, usually the tasks of seismic interpretation are mostly based on the seismic structural image (i.e. the angle-averaged reflectivity), optionally accompanied with seismic attribute information (Chopra & Marfurt, 2007). Alternatively, the reservoir characterization is usually based on AVO information in some pre-stack domain (e.g. via the angle-gathers), see e.g. (Veeken & Rauch-Davies, 2006). The latter usually employs the 1.5D assumption, meaning that locally a 1D medium is considered in order to use the Zoeppritz equations or its approximations (Aki & Richards, 1981), even if the inversion is done in a full waveform manner (Gisolf & van den Berg, 2010).This means that local heterogeneity is usually not properly incorporated, as there is no proper forward model describing the AVO response in a laterally inhomogeneous medium (Hammad & Verschuur, 2019). However, the heterogeneity information is encoded in the angle-dependent response, e.g. by an non-symmetric behavior for positive and negative angles of incidence, which is neglected in the Zoeppritz equations for PP reflectivity.

In this paper we propose a procedure to incorporate this detailed information on heterogeneity via a Deep Learning approach. For this, we assume a few geological scenarios and generate seismic forward data for each of them. An angle-dependent full-wave migration (FWM) is applied to generate seismic images (Davydenko & Verschuur, 2017). To access the encoded information, FWM can produce subsurface Radon gathers using the extended image domain. Following that, a multilabel machine learning (ML) network is trained using these gathers from a selection of models related to a few possible geologic scenario. The network determines for each subsurface area which scenario is most comparable to the input. By using this hybrid workflow, we hope to go beyond deterministic imaging, characterization limits and step forward overcoming the common problems for stratigraphic architecture imaging.

Proposed workflow

In this study, there are three stages of data generation, image domain encoding, and machine learning to the process (***Figure 1***). Next, we introduce each stage separately and then progressively associate them. We will directly link this description to a first, basic example to illustrate the procedure.

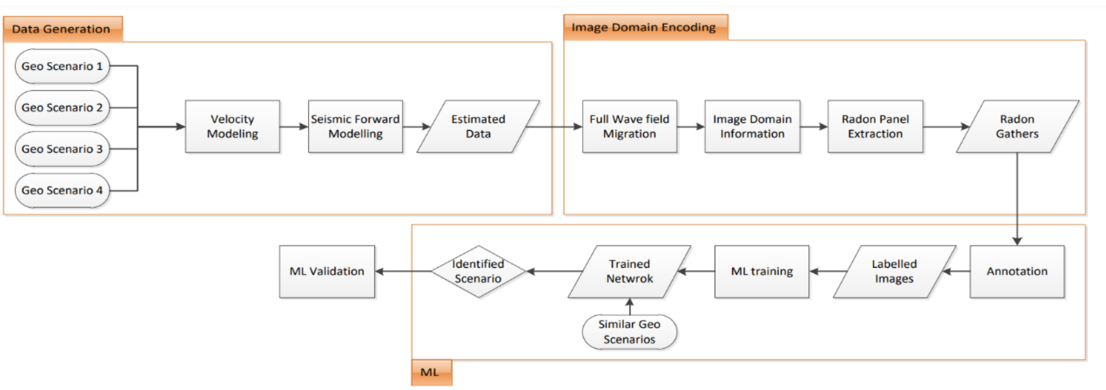


Figure 1 *Proposed hybrid FWM-ML workflow.*

Data Generation

For the first stage, the procedure begins by defining (for our current example) four typical types of stratigraphic architecture called geo scenarios, as shown in ***Figure 2***. These scenarios are stratigraphic "Fluvial system" "Clinoforms","Alluvial fans", " Coarsening upwards trends". A correspondence velocity model is then constructed for each scenario (***Figure 3***), and finally their forward seismic date is generated with a finite difference method. For this first simple example, we do not yet include an overburden to each model.

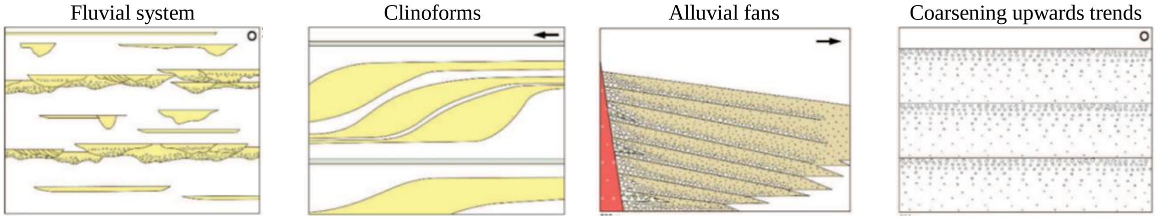


***Figure 2** Four main scenarios of stratigraphic structures- Geo models.*

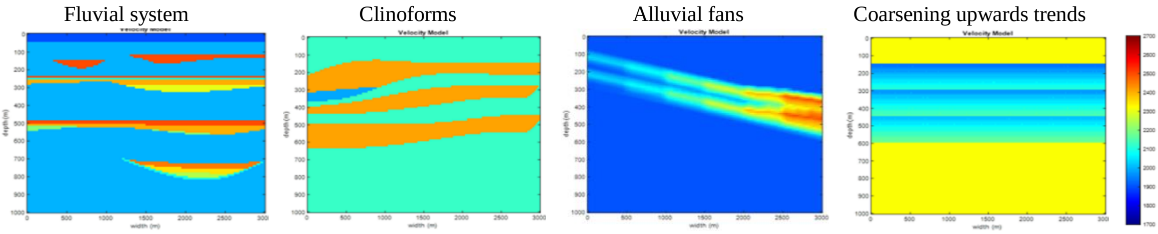


***Figure 3** Four main scenarios of stratigraphic structures- Velocity models.*

Image Domain Encoding

The application of FWM to the estimated data initiates the second stage. Through this process, time domain data is converted to some extended image domain by inversion techniques. In this stage, after the generation of images with angle-dependent FWM mode (***Figure 4***), the Radon panel cube is calculated and serves as the representative of the wave's angle-dependent characteristics (***Figure 5***). It is important to mention that despite the fact that each of these Radon panels corresponds to one lateral location, they all carry information about the locations nearby (Davydenko & Verschuur, 2017). Such that they can serve as input for deep learning networks to recognize lateral heterogeneity.

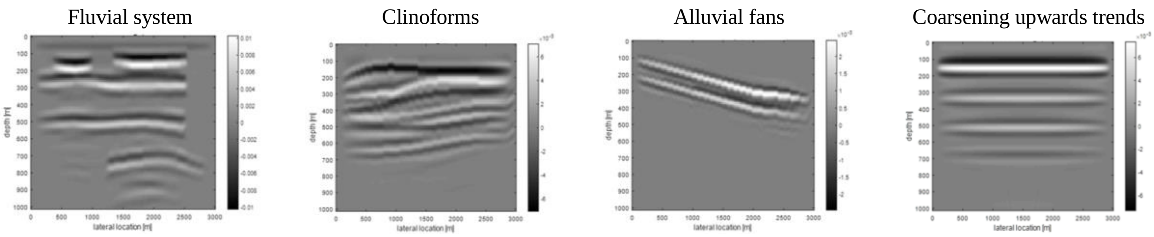


***Figure 4** Four main scenarios of stratigraphic structures- Subsurface images.*

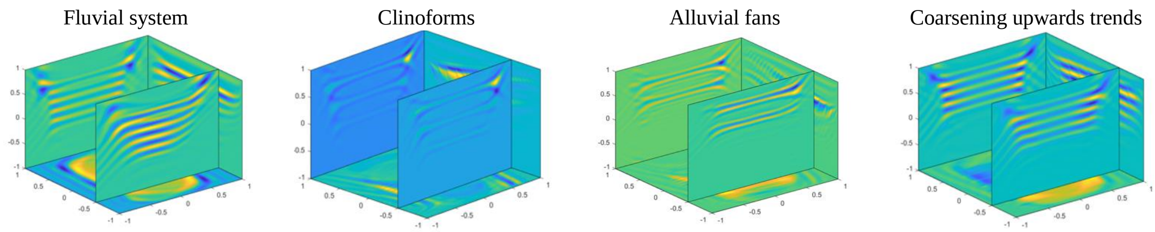


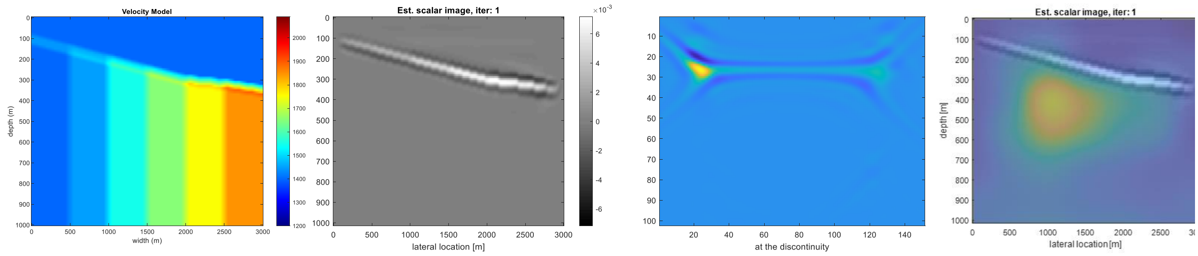
***Figure 5** Four main scenarios of stratigraphic structures- Radon Panel cubes.*

Hybrid FWM-ML

The third phase addresses the ML deployment as follows. The information on heterogeneity and fine-scale features that are not visible in the image itself, is contained in the Radon gathers. The patterns related to these geologic structures cannot be understood by visual perception alone (Li, 2018; Pintea, et al., 2021). It is worth noting that the 1.5D medium assumption produces symmetric patterns in Radon panels, whereas heterogeneity produces asymmetric PP-reflectivity patterns. As a result, in this research, we suggest a combination of angle-dependent FWM to extract the Radon gathers and ML to recognize the patterns from these gathers. The ML part attempts to understand the pattern associated with each geologic scenario and train the network using it. This ML network classifies images locally into one of four classes using the multiclass classification technique. In contrast to standard binary and multiclass classification, this machine learning network predicts the likelihood of each class in this classification (Sokolova & Lapalme, 2009). Following the detection, the network provides a similarity rate score between the scenario classes and the detected class. Finally, gradient-weighted class activation mapping (Grad-CAM) is used to designate which portions of the image are used by the network for each of the true classes (Sokolova & Lapalme, 2009).

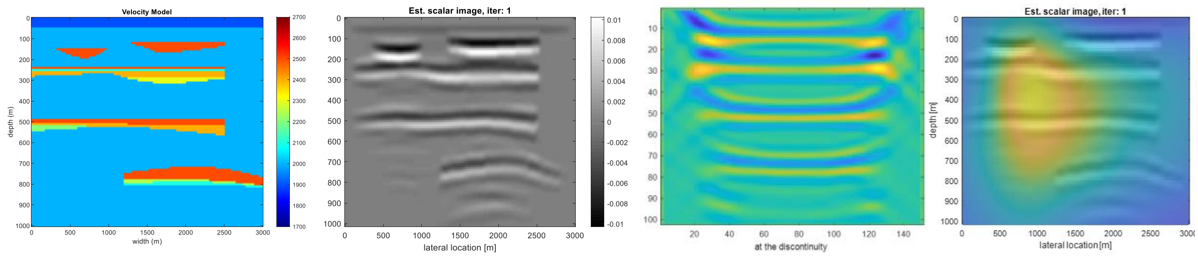
Validation model

For network validation proposes, similar stratigraphic scenarios models with variations were developed. These newly developed geological models were different in terms of velocity range and pattern, but they followed the similar geologic criteria for the stratigraphic structures. For example, consider the geological model depicted in ***Figure 6*** (a), which is a representative of Alluvial fans. The layers thickness of this unrealistic geological model was assumed to be infinite. The goal of selecting this model was to specify how well the trained network is capable of recognizing the class. To do that the forward seismic generation, and FWM-angle dependent was generated (***Figure 6*** (b)). Consequently, the Radon panels for each surface location were determined (***Figure 6*** (c)). Each location panel was analyzed with the ML network and the image and final similarity detection map was overlaid in ***Figure 6*** (d). The final detection result revealed that the network is certain that "stratigraphic type - Fluvial system" exist. As shown in ***Figure 6*** (d), the maximum likelihood also happens in between 500 and 1500 meter. The validation model in ***Figure 7*** is comparable to a fluvial system, with the exception that the deposited sediment in the bottom half, unlike the common deposit, is convex in shape. The network identified the class and stated that the maximum likelihood occurs before the starting point of the convex shaped deposit (***Figure 7*** (d)).



(a) Velocity model (b) Image (c) A Radon panel for location 1500 (m) (d) Image overlaid with similarity map Grad-Cam

Figure 6 *First validation model.*



(a) Velocity model (b) Image (c) A Radon panel for location 1500 (m) (d) Image overlaid with similarity map Grad-Cam

Figure 7 *Second validation model.*

Discussions and conclusions

This research focuses on developing a method to categorize stratigraphic formations using a machine learning network trained with angle dependent image information generated by FWM. These gathers served as the network's input. Following the training phase, the network was validated using a number of similar model angle gathers. With a scoring system that compares the detected class to the training class, the network demonstrate its ability to detect the class. Furthermore, a guidance map depicting the maximum chance between these two aids in best match locations. It is worthy to mention, the main advantage of this method is its ability to retrieve structures beyond the 1.5D assumption typically embedded in reservoir characterization. We also hope to go beyond standard seismic resolution. This finding agrees with the results of previous studies, which suggested Radon gathers could identify generalized transfer functions that are not normally extracted with common methods. Furthermore, in contrast to other studies, the proposed method proves to classify the stratigraphic structure for these four geologic scenarios. Further studies are necessary to confirm the findings of this study. First of all, we need more models per geologic scenario and also have to include realistic overburdens. Next, we suggest further studies with more geological scenarios. Besides, a feasibility study on using other annotated inputs, such as subsurface offset gathers, can reveal crucial information. Finally, we recommend that future research use real datasets to test the accuracy of the suggested strategy.

Acknowledgements

The authors would like to thank the members of Delphi consortium for their support.

References

Aki, K., & Richards, P. G. (1981). *Quantitative Seismology: Theory and Methods* . University Science Books.

Chopra, S., & Marfurt, K. J. (2007). *Seismic Attributes for Prospect Identification and Reservoir Characterization.* SEG Geophysical Developments Series.

Davydenko, M., & Verschuur, D. J. (2017). Full-wavefield estimation of angle-dependent reflectivity and migration velocity. *SEG Technical Program Expanded Abstracts* (pp. 5631-5635). SEG.

Gisolf, A., & van den Berg, P. M. (2010). Target Oriented Non-linear Inversion of Seismic Data. *EAGE Conference & Exhibition* (pp. 2860-2864). European Association of Geoscientists & Engineers.

Hammad, H. I., & Verschuur, D. J. (2019). Slowness and Reflection Coefficient Curves for Laterally Heterogeneous Media. *81st EAGE Conference and Exhibition* (pp. 1-5). European Association of Geoscientists & Engineers.

Li, W. (2018). Classifying Geological Structure Elements from Seismic Images Using Deep Learning. *SEG Technical Program Expanded Abstracts*, (pp. 4643-4648).

Pintea, S. L., Sharma, S., Vossepoel, F. C., van Gemert, J. C., Loog, M., & Verschuur, D. J. (2021). Seismic inversion with deep learning. *Computational Geosciences, 26*, 14.

Sokolova, M., & Lapalme, G. (2009). A Systematic Analysis of Performance Measures for Classification Tasks. *Information Processing & Management*, 427–437.

Veeken, P., & Rauch-Davies, M. (2006). AVO attribute analysis and seismic reservoir characterization. *First Break*, 41-52.