Delft University of Technology

Lithology Prediction from the Results of Full Elastic Wave-equation based Inversion Scheme

Feng, Runhai; Luthi, Stefan; Gisolf, Dries; Sharma, Siddharth

DOI
10.3997/2214-4609.201601388

Publication date
2016

Document Version
Final published version

Published in
78th EAGE Conference and Exhibition 2016, Vienna, Austria

Citation (APA)
Feng, R., Luthi, S., Gisolf, D., & Sharma, S. (2016). Lithology Prediction from the Results of Full Elastic Wave-equation based Inversion Scheme. In *78th EAGE Conference and Exhibition 2016, Vienna, Austria* (pp. 1-5). EAGE. https://doi.org/10.3997/2214-4609.201601388

Important note
To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Copyright
Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy
Please contact us and provide details if you believe this document breaches copyrights.
We will remove access to the work immediately and investigate your claim.

This work is downloaded from Delft University of Technology.
For technical reasons the number of authors shown on this cover page is limited to a maximum of 10.

Th P2 06

Lithology Prediction from the Results of Full Elastic Wave-equation based Inversion Scheme

R. Feng* (Delft University of Technology), S.M. Luthi (Delft University of Technology), A. Gisolf (Delft University of Technology) & S. Sharma (Delft University of Technology)

SUMMARY

Inversion results from seismic data of a synthetic example based on the Cretaceous fluvio-deltaic Book Cliffs outcrops in Utah (USA) have been used to extract the reservoir parameters. The input data sets are compressibility and shear compliance which are from the full elastic wave-equation based inversion method. A fuzzy logic inference algorithm has been applied in which the lithology templates are based on well-logging data. The membership functions of the lithologies are constructed firstly. Then inversion results are used to predict the reservoir lithology. It is suggested that this classification method performs well because most of the time the same or similar lithologies have been predicted. However, this approach heavily depends on the input inversion results and therefore the full elastic wave-equation based inversion has been chosen.

Introduction

Reservoir characterization is an important step in the development of hydrocarbon reservoirs. A reliable reservoir model should combine information of different sources and is then used to predict the performance of the reservoir after flow simulation. Nowadays, the data used in the reservoir characterization include core samples, well-logging, seismic data, etc.. The first two will provide high-resolution information while the third one has a resolution in tens of meters.

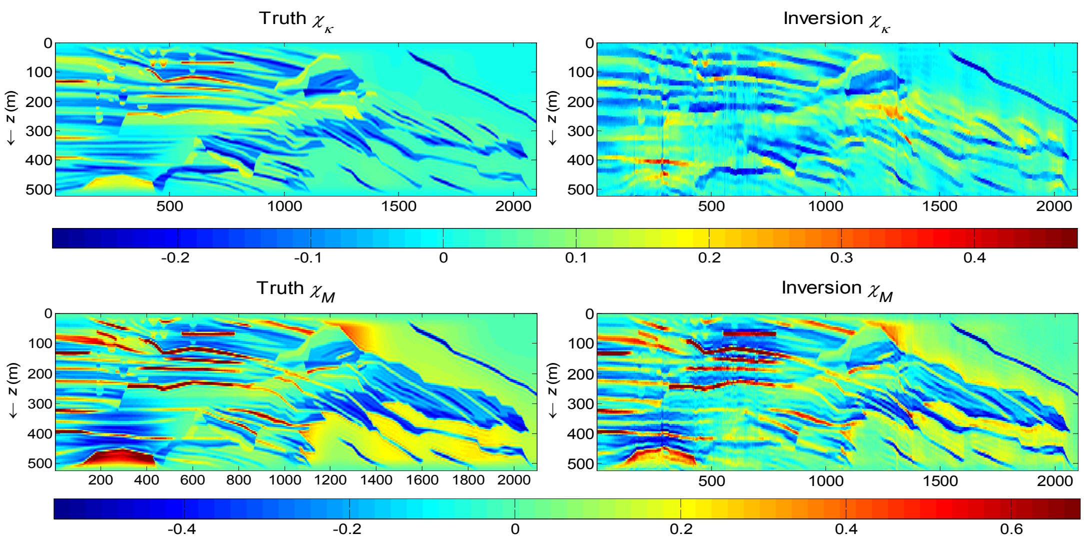
However, core samples and well-logging data are only available at selected locations which means they cannot give full 3D information of the reservoir. On the other hand, seismic data frequently provide a 2D or 3D coverage over a large area, and thus can be utilised to make a structural picture of the reservoir (Artun *et al*., 2005). Hence, efforts have been geared toward the usage of inversion results from seismic data in reservoir description. A full-waveform inversion scheme can provide high resolution results, because the intrinsic non-linear relationship between rock properties and seismic data has been exploited (Gisolf *et al*., 2014). This feature makes it suitable as a potential input for the reservoir characterization process.

In this paper, the results from the full elastic wave-equation based inversion scheme (Feng *et al*., 2015b) are going to be used as input for reservoir characterization.

Since there is invariably some degree of uncertainty and unreliability even with the chosen inversion method, a fuzzy logic inference scheme is used to predict the lithologies. Compared to other methods, this inference engine can better handle the vagueness and imperfectly defined knowledge, which makes it more robust and easier to quantify the confidence of the analysis (Saggaf and Nebrija, 2003).

Elastic Wave-equation based Inversion

The inversion algorithm we use was developed by Gisolf & van den Berg (2010a) and has been extended to elastic which means the converted waves will also be used in the inversion process. In this method, the well-known P and S velocities are broken down into true elastic properties, notably the compressibility $\kappa = 1/K$ (with K being the bulk-modulus), and the shear compliance $M = 1/\mu$ (with μ being the shear modulus). Instead of inverting for κ, M and ρ, the contrast functions based on the backgrounds (κ_0, M_0, ρ_0) are solved for, at every location. The detailed theory of the inversion method is described in Gisolf and van den Berg (2010a) and Gisolf *et al*. (2014). Here only the inversion results are shown in Figure 1 in terms of the contrasts in compressibility, shear compliance and bulk density (χ_κ, χ_M, χ_ρ).



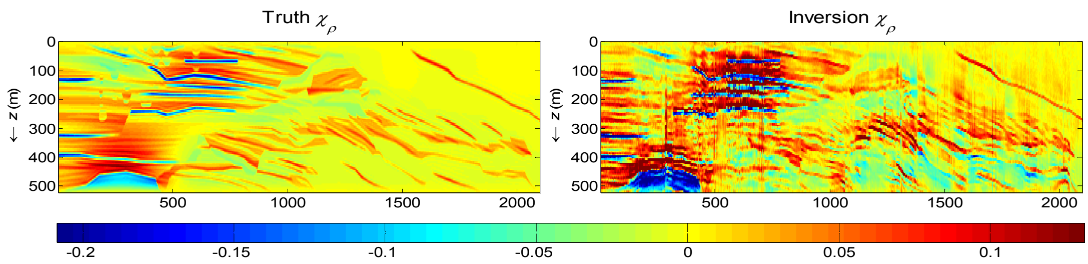


***Figure 1** The true and inverted results for the contrasts in compressibility, shear compliance and density (χ_κ, χ_M, χ_ρ).*

Lithology Prediction by Fuzzy Logic Inference

The inversion results, whether in terms of velocity and density or compressibility and shear compliance, are not what the reservoir specialists can easily relate to. These results need, therefore, to be transformed to reservoir properties such as lithology, porosity and permeability, by incorporating core and well-log information which are typically few in any given oilfield because of their high cost and impracticality. Of the different mathematical methods, the fuzzy logic inference is chosen to model the relationship between seismic inversion results and reservoir lithologies, because of its better performance in the investigation of uncertainty, which is intrinsic in geological data (Saggaf and Nebrija, 2003).

In order to build the membership function that is used to characterize the degree to which a certain observation belongs to the fuzzy set, the properties of well logs in terms of κ and M are utilized (Figures 2 and 3). At this moment, the inversion result of density is not considered because it is very poor (Figure 1).

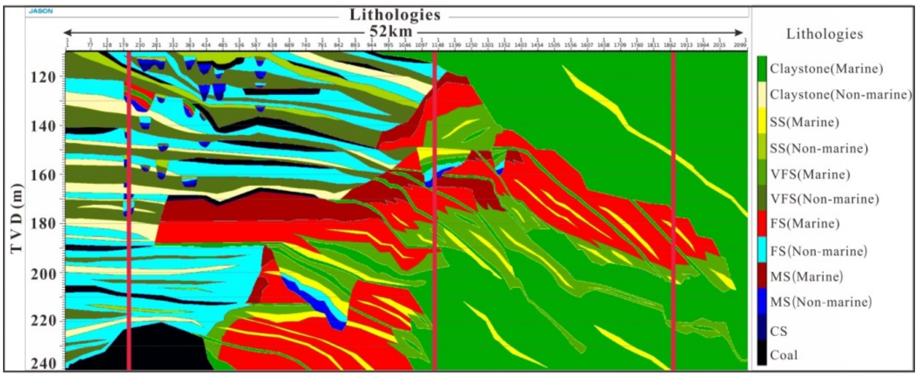


***Figure 2** The locations of well logs (CMP=185, 1130, 1880).*

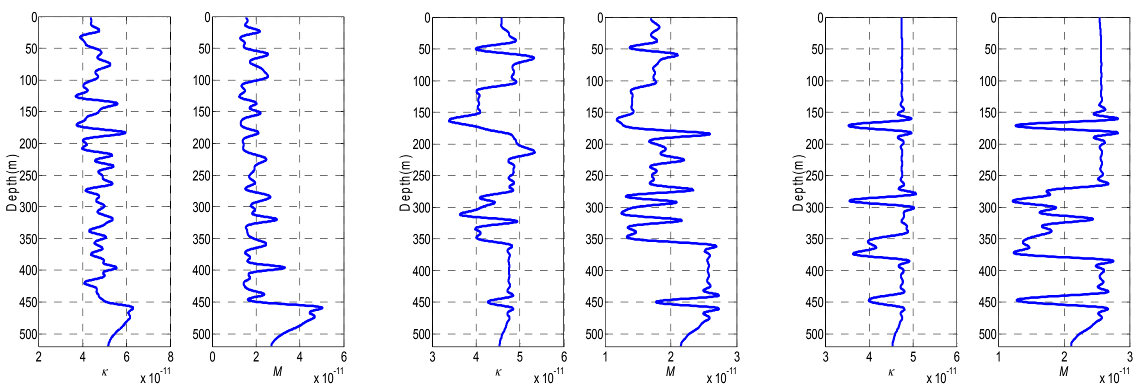


***Figure 3** The property values in terms of* κ and M *(From left to right, CMP=185, 1130, 1880).*

After training, the membership function of the twelve lithologies, for which the unnormalized double Gaussian function has been selected, are shown in Figure 4.

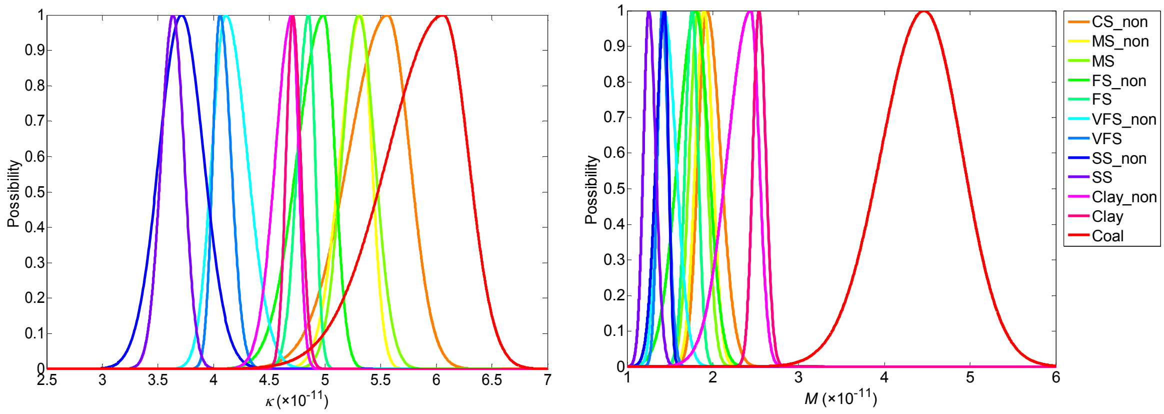


Figure 4 *The membership functions of twelve lithologies.*

Then the inversion results are used to predict the reservoir lithologies where it has not been cored or logged. Figure 5 is showing the inversion results at CMP 100.

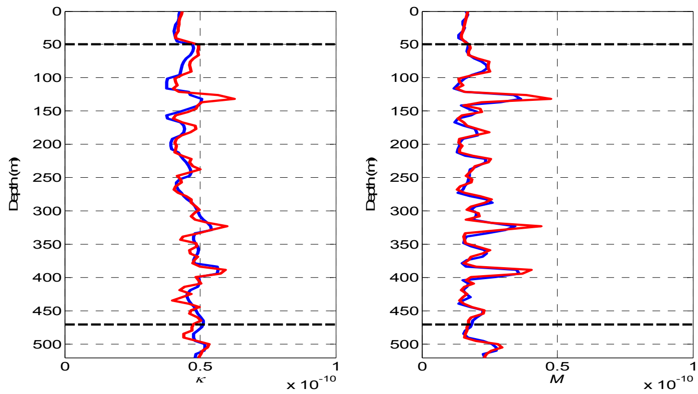
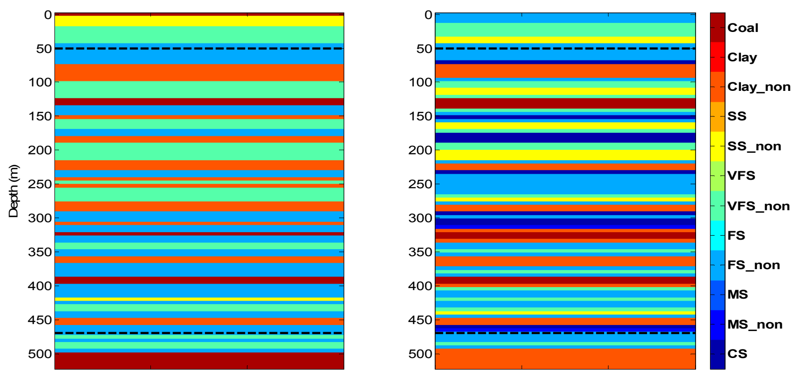


Figure 5 *The inverted and true properties at CMP=100 (Blue curve is the inversion, red is the truth).*

The lithology prediction is shown in Figure 6(b). Only the interval between the dashed lines is considered.



(a) *(b)*

Figure 6 *The predicted lithology with inverted data. The dashed black lines are the tapering boundaries in the forward model. (a) for truth, (b) for prediction.*

Discussion and Conclusion

In this paper we have used the results from elastic wave-equation based inversion as input for the prediction of reservoir parameters. The fuzzy logic method has been selected as the approach in which input data have been fuzzified firstly, then the membership function is built and the combination operator is used to mix the possibilities in order to defuzzify the output results.

The reservoir oriented elastic wave-equation based inversion scheme can take care of internal multiple scattering as well as wave-mode conversion, which makes recovery of broadband properties and high resolution possible. These broad-band properties are suitable as input for the prediction of reservoir lithology. Compared to cored or logged wells, seismic inversion has a much larger coverage and can even provide 3D or 4D information, which makes it a good tool for reservoir characterization. The information from cored or logged wells is used as lithology template and is used to build membership functions for the fuzzy logic procedure. By contrast to other methods used in reservoir characterization such as statistical empirical equations or neural networks, the fuzzy logic inference is simple to comprehend and the geological prior information can be plugged easily into it.

The inversion results of one single CMP have subsequently been utilised for validating and testing. In Figure 6, between depths from 240m to 270m, the Very-Fine-Sandstone_non_marine has been wrongly predicted as Fine-Sandstone_non_marine, which is acceptable since both of the lithologies are close to each other and have similar reservoir properties. However, in the prediction the Siltstone_non_marine has been assigned erroneously at depths such as 120m, 160m, 200m, which can be attributed to the imperfect inversion results. This also happens to coal prediction at depths 140m, 330m which are thicker than the truth. It can be argued that inversion of M is almost the same with the truth (Figure 5) but the classification is not as good. The reason for this is the combination operator in the fuzzy logic, which we used between κ and M, because it does not put as much emphasis on the latter as expected. Therefore, in a further step a better combination operator should be designed. Bringing the geological knowledge or other information from petrophysics into the fuzzy logic approach, could make the prediction more accurate and should be part of the future plan.

Until now, only lithology has been classified, which is insufficient for reservoir characterization. The other important properties include porosity and permeability and they should be quantified as the next step based on the inversion results. Then the inversion of density could be incorporated, because it has a close relationship with porosity and may improve the prediction result.

Acknowledgments

This study is supported by the DELPHI Consortium.

References

Artun, E., *et al*. [2005] Reservoir Characterization Using Intelligent Seismic Inversion. *SPE Abstracts*, *SPE Eastern Regional Meeting*, West Virginia (USA), SPE-98012-MS.

Feng, R., *et al*. [2015b] An outcrop-based detailed geological model to test automated interpretation of seismic inversion results. *EAGE Expanded Abstracts*, *77th EAGE Conference & Exhibition*, Madrid (Spain), N102.

Gisolf, A. & van den Berg, P.M. [2010a] Target oriented non-linear inversion of seismic data. *EAGE Expanded Abstracts*, *72nd EAGE Conference & Exhibition*, Barcelona (Spain), P308.

Gisolf, A., *et al*. [2014]. Non-linear full wavefield inversion applied to carboniferous reservoirs in the Wingate Gas Field (SNS, Offshore UK). *EAGE Expanded Abstracts*, *76th EAGE Conference & Exhibition*, Amsterdam (Netherlands), E106.

Saggaf, M. M. & Nebrija, E. L. [2003] A fuzzy logic approach for the estimation of facies from wire-line logs. *AAPG Bulletin*, **87**(7), 1223-1240.