Estimating porosity of carbonate rocks using sequentially applied neural network based, seismic inversion.

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Summary

In this case study, an inversion problem, that is too complex for a single step neural network based inversion to solve, is solved by breaking the problem into a series of nested inversions. The raw data input is post-stack seismic data and the desired output is a porosity volume. The porosity data is calculated from geophysical logs that were collected in wells located within the extent of the seismic volume. The developed workflow, that successfully solves the problem, turns out to be very similar to the deep learning process developed in Artificial Intelligence computer applications.

Introduction

The purpose of this study, was to investigate the performance of a workflow built on a neural network based seismic inversion methodology. The challenging aspect of the project was that the lithological environment consisted of carbonate rocks with various amounts of porosity, carbonates mixed with shale, anhydrite and halite beds. The combination of these lithologies result in acoustic impedance values that are very similar. The seismic data used in the study is a pre-stack time migrated volume.

Porosity in twenty five wells, located within the 3D seismic volume, was estimated using a multi-mineral and multi-fluid analysis methodology. A mineralogical model, that included the rock matrix and formation fluid, was established and its volumes were optimized to match the observed well log responses using the optimizing petrophysics approach Figure 1 (Mayer and Sibbit, 1980). The calculated porosity curve was the target property to be obtained by inversion from the seismic volume.

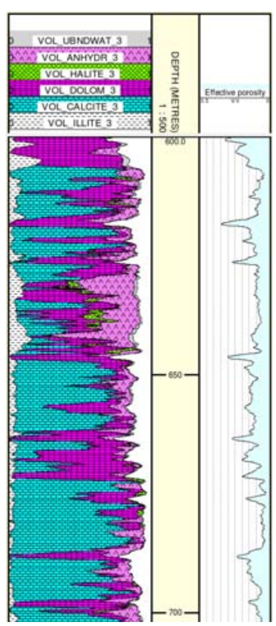

Figure 1 Plot of mineralogy and porosity obtained using well log inversion.

The petrophysical relationship between Porosity, Gamma Ray (GR) log, and Acoustic impedance are displayed in Figure 2. The relationship is fairly complex due to variable mineralogy and porosity, as mentioned previously.

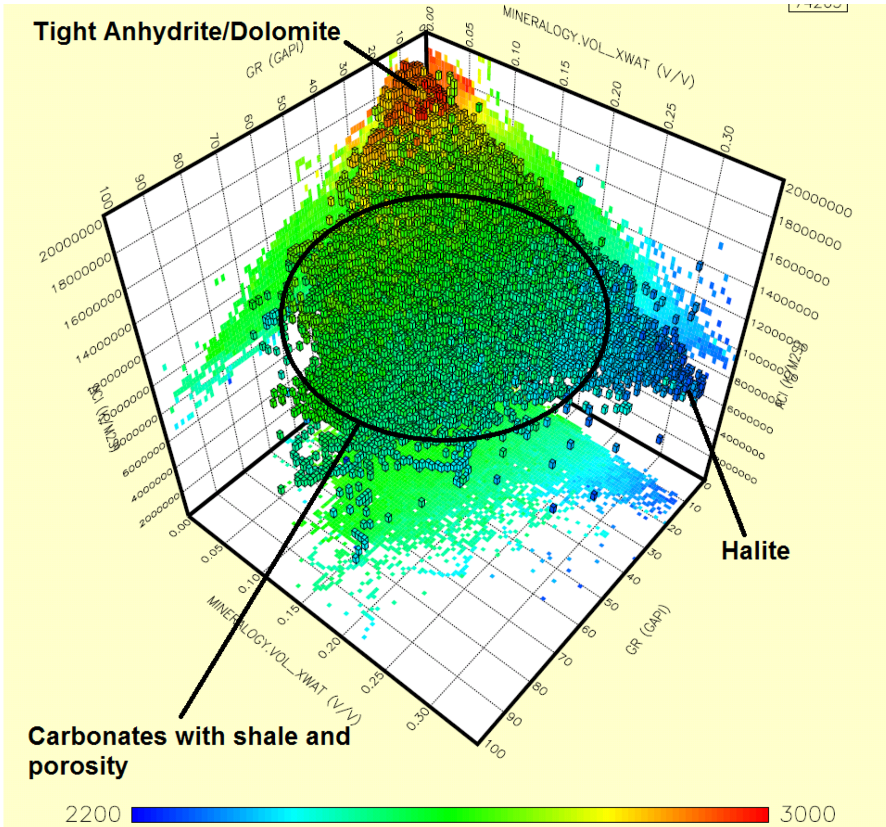

Figure 2 GR, Porosity (XWAT) and acoustic impedance relationship. The dots are coloured by density. The horizontal axes are GR and porosity, the vertical axis is acoustic impedance. The different lithologies are marked.

The porosity correlates poorly with the acoustic impedance due to the presence of halite beds and shale that is mixed with the carbonates.

Methodology

The first attempt to extract porosity information from the seismic data was done using a conventional workflow: first running a post-stack inversion to obtain an impedance volume and then using the multi-attribute transform followed by neural network prediction (Hampson el al. 2001). This resulted in a poor correlation between the well data and predicted porosity with a correlation coefficient of 0.4.

To improve the results, a step by step workflow was derived (Figure 3). The workflow consists of the following steps:

1. Post-stack inversion to generate an Impedance volume.
2. Apply the Multi-Attribute Analysis - Neural Network (MAA-NN) process to generate a high resolution impedance volume.

3. Generate a high resolution density volume using the MAA-NN process by supplying the high resolution impedance volume as an additional attribute.
4. Generate a high resolution gamma ray volume using the MAA-NN process by supplying the high resolution impedance volume and density volume as additional attributes.
5. Generate a high resolution porosity volume using the MAA-NN process by supplying the previously obtained high resolution impedance, density and gamma ray volumes as additional attributes.

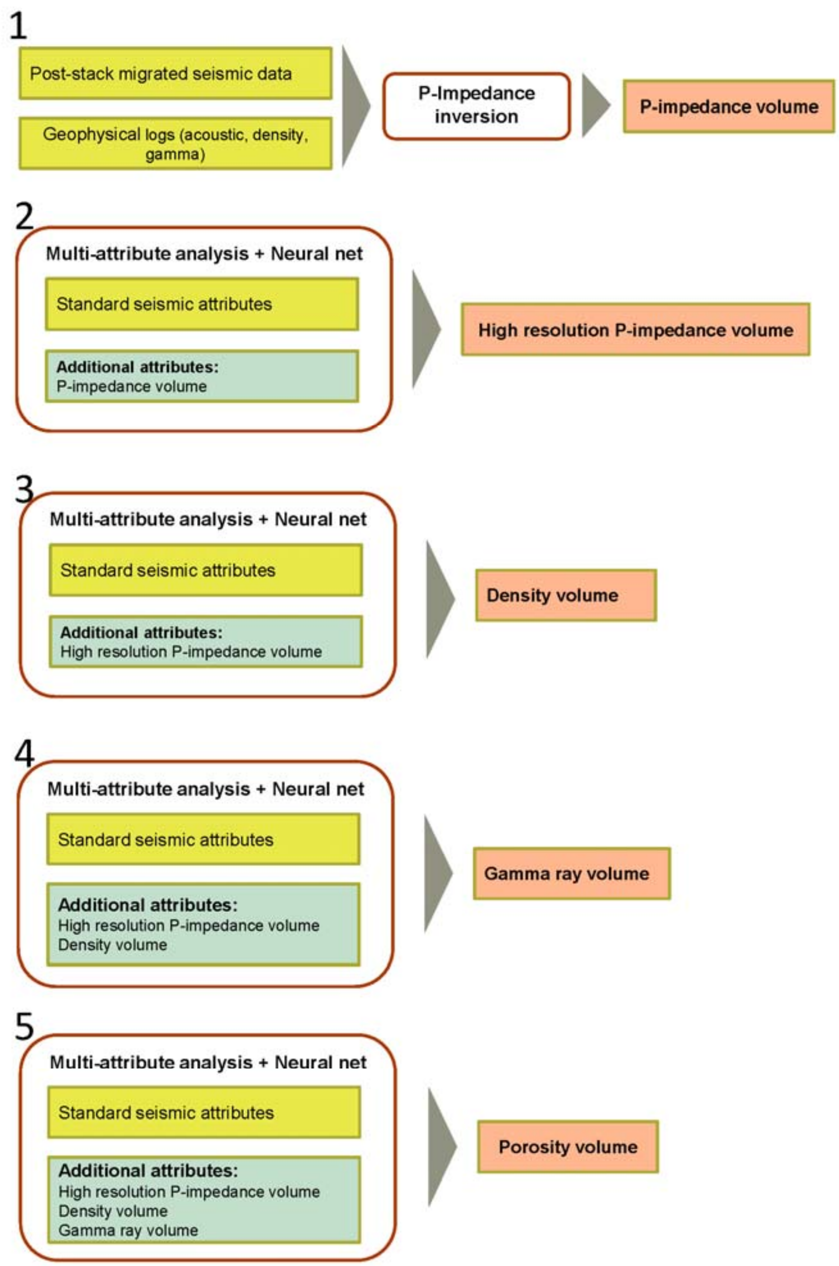

Figure 3 Final workflow. See text for details.

The workflow generates very good results with excellent correlation between the well data and porosity predicted from seismic (Figure 4, Figure 5).

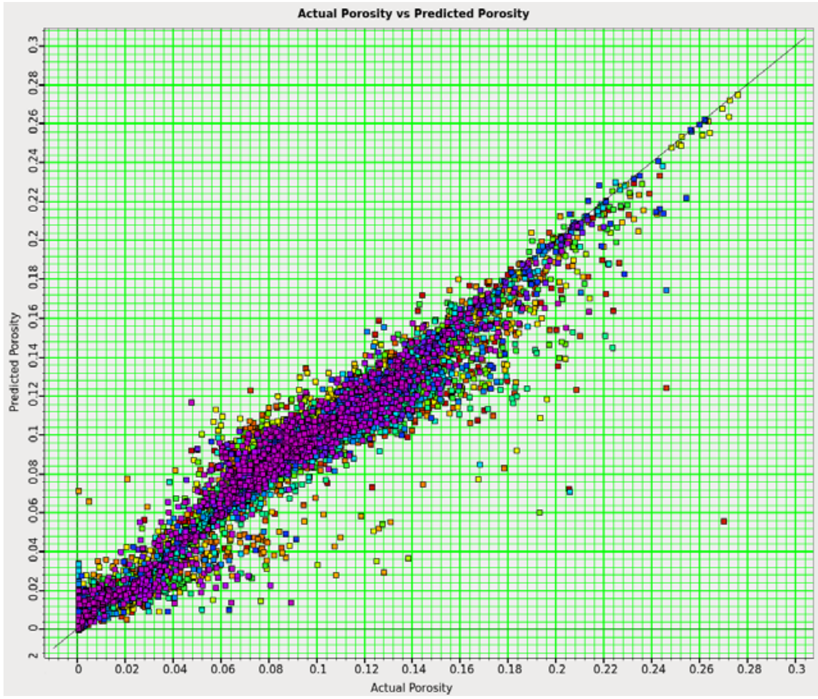

Figure 4 Actual vs Predicted porosity as plotted at the wells locations. The correlation coefficient is 0.97

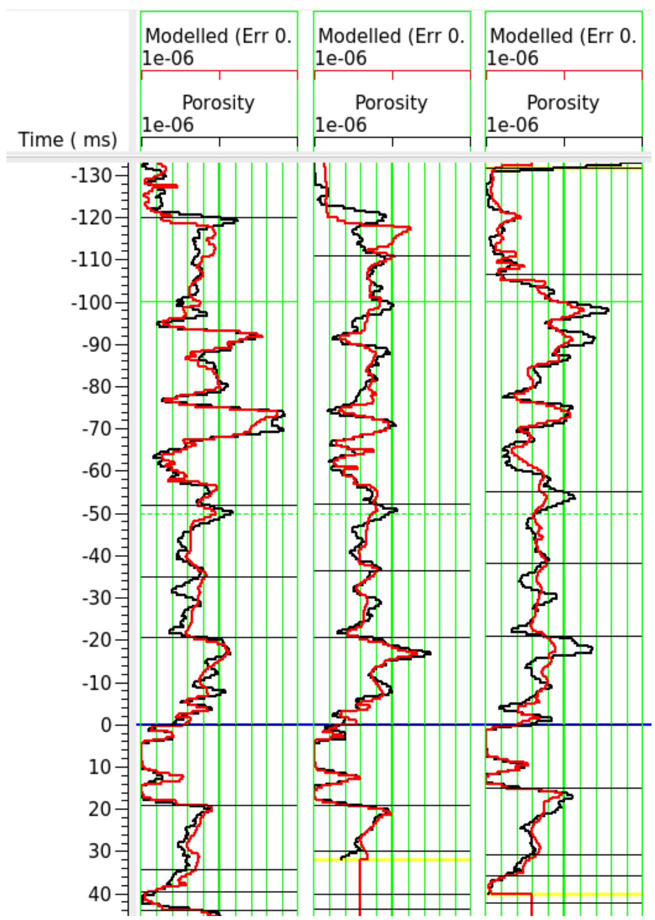

Figure 5 Validation plot showing the porosity at the wells (black) and porosity predicted from seismic (red).

Conclusions

The developed workflow successfully estimates porosity from post-stack seismic data in a lithologically complex environment. The key component of the workflow is to sequentially derive physical attributes and provide them as input to the next step of the inversion MAA-NN process. The selection of the type of physical attributes is based on petrophysical analysis of well log data and their suitability in separating lithological components. The developed workflow turns out to be similar to the deep learning process developed for Artificial Intelligence applications (Goodfellow et. al.). The deep learning process breaks down a problem, which is too complex for neural networks, into simpler problems (representations) that are solvable. Each step in the developed workflow corresponds to simple mappings, that when combined together as a sequential process, perform the complicated mapping. In the provided example the deep learning process consists of four layers in a sequence:

1. Derivation of the high resolution impedance volume.
2. Derivation of the high resolution density volume.
3. Derivation of the high resolution gamma ray volume.
4. Derivation of the high resolution porosity volume.

The results of each layer are provided to the next layer as inputs to provide the final porosity volume.

Acknowledgements

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References

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