2011 CSPG CSEG CWLS Convention

Application of Neural Network Analysis and Post-Stack Inversion - Case Studies in Alberta

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Summary

We estimate the P-impedance from the post-stack data by way of model based inversion as well as neural network analysis. We are showing comparisons of the results obtained from two areas in Alberta, Canada. The comparison shows that the two methods of impedance estimation compare well in their low frequency trends. However, the neural network analysis provides more subtle information of the impedance structure that is consistent with the local geology.

Introduction

Model based inversion is routinely done to obtain information about the subsurface impedance structure at and around the reservoir level. The usual practice is to obtain an estimate of the embedded wavelet and recursively update a suitably chosen impedance profile so as to minimize the data misfit criterion. The initial model is generally obtained from well logs by interpolation over the entire volume and subsequent application of low pass filter (10-15 Hz). The updated model corresponding to the minimum of the data misfit criterion is considered to be the accepted P-impedance structure within the zone of interest.

Neural networks have been in use for geophysical applications since early 1990s. McCormack (1991) describes some of the early geophysical applications of neural network by predicting lithology log for an entire well, using back-propagation Multi-Layer Feed Forward Network (MLFN). Subsequent to this work, Schultz et al. (1994) proposed the application of neural network in estimating the log properties from the seismic data in a data-driven interpretation framework. Liu and Liu (1998) applied the neural networks for the inversion of sonic and shale content logs using well-log and seismic data.

The P-impedance can be estimated by neural network analysis. We use the probabilistic neural network (PNN) architecture for the analysis. The neural network is trained and validated for estimating P-wave velocity and density over the zone interest. The estimated P-wave velocity and density are subsequently used to compute the P-impedance. This article shows application of neural network based estimation of P-impedance with two case studies from Alberta and a comparison is made with the conventional model based inversion of impedance.

Method

The neural network analysis estimates the target log by making use of several attributes chosen from a suite of attributes. The selection of optimum number of attributes is usually done by the linear multi-attribute regression analysis. Also in order that the seismic data and the target well logs are scaled to the same resolution level, a convolutional approach is used for estimation of the target logs (Hampson et al. 2001).

The optimum number of attributes and the operator length for each of the P-wave velocity and density estimation are obtained from the linear multi-attribute regression analysis. The optimum attributes and the operator length thus obtained are subsequently used to train the probabilistic neural network. The trained network is further validated by computing the prediction error between the target log and the predicted log by sequentially hiding the target logs. The trained and validated network is subsequently applied over the entire 3D data volume to individually estimate the P-wave velocity and density parameters for each of the data volumes under study. The estimated P-wave velocity and density are used to compute the P-impedance over the two 3D volumes from Alberta. Figure 1 illustrates this workflow.

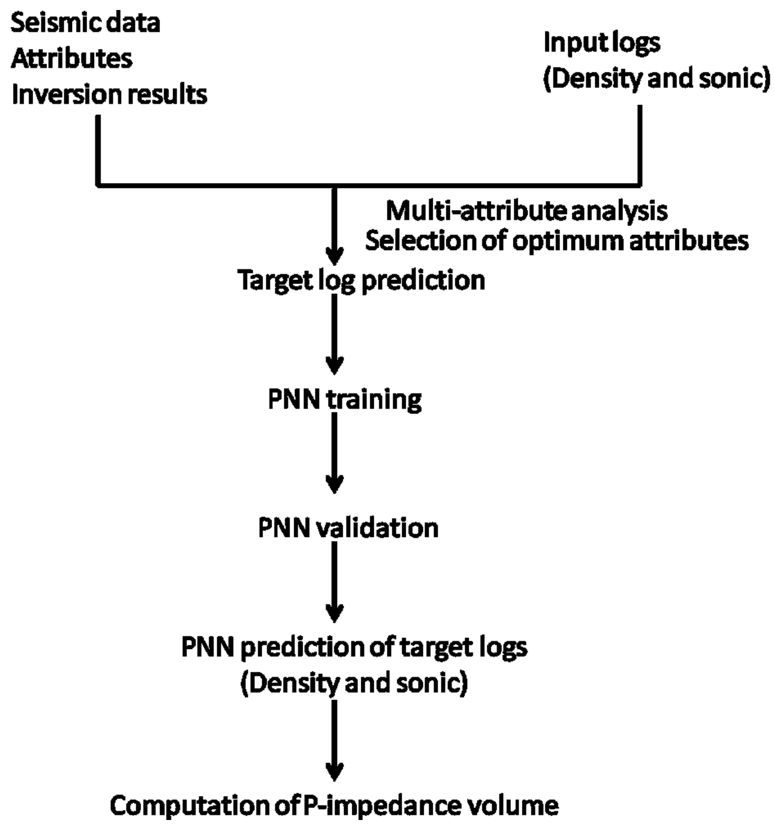

Figure 1: Workflow for neural network estimation of P-impedance

Examples

We applied the above methodology to two different data volumes from Alberta, Canada. The first case study shows data volume acquired over north-central Alberta and the second case study shows the data volume acquired over south-central Alberta. The results are described below.

Case study I

Figure 2(a) shows the conventional P-impedance obtained from the model-based post-stack inversion. Figure 2(b) shows the PNN analysis based P-impedance estimation. The two inserted black curves represent the P-impedance logs. It can be noticed that the general low frequency trends in the two figures compare well with each other. However, the analysis with PNN provides more detailed impedance profile information compared with conventional inversion and which in turn correlates well with the impedance logs. The elliptical zone shown in the figure lies within the shale play. The conventional post-stack inversion shows that most of this zone has low impedance and hence porous. This result is not consistent with the well log. The PNN analysis shows tight shale zone sandwiched between thin porous layers. This is consistent with the well log information.

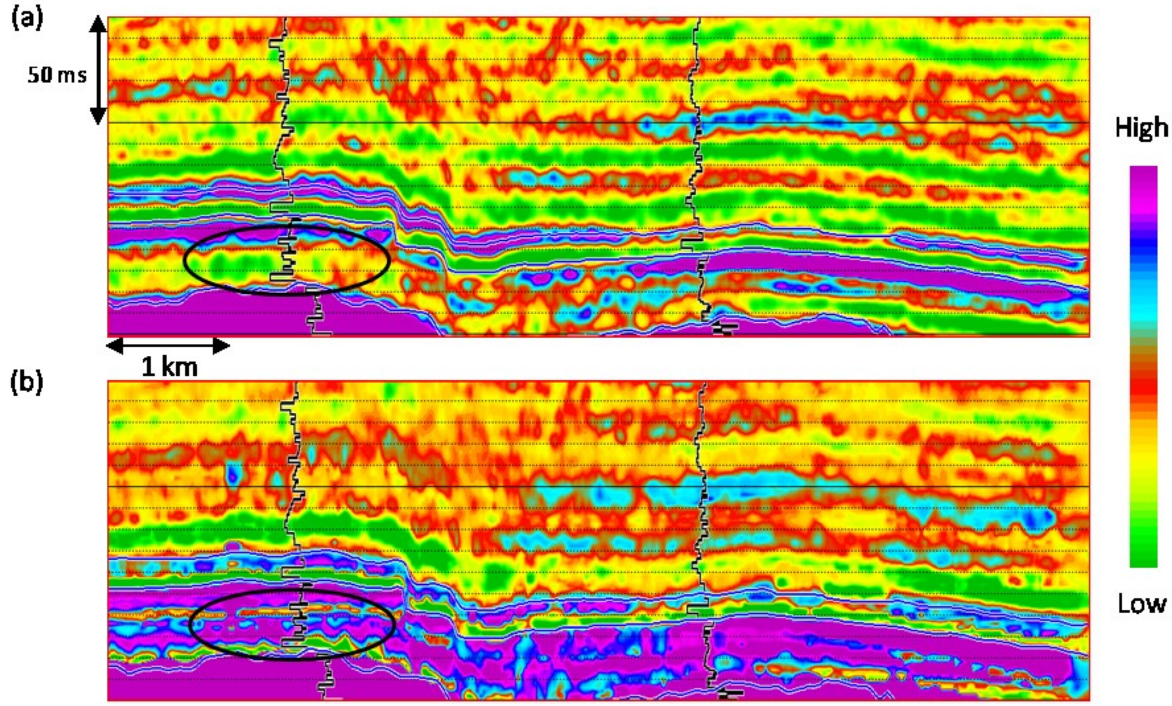

Figure 2: (a) P-impedance obtained from model-based post-stack inversion. (b) P-impedance obtained from PNN analysis. P-impedance logs at two locations are inserted. The black ellipse shown in the figure shows the zone of shale play. Notice the detailed and accurate correlation of the impedance values with the impedance log curves as seen on the neural network estimated impedance.

Case study II

Figure 3 shows the results for the second case study. Figure 3(a) shows the P-impedance obtained from the model-based post-stack inversion. Figure 3(b) shows the P-impedance estimated by the PNN analysis. The inserted black curve is the P-impedance log. As in the previous case study, it is noticed that the general P-impedance trends are comparable with each other. However, the result obtained with the PNN analysis show more detailed information about the subsurface impedance structure. Furthermore, the well logs correlate well with the result obtained from the PNN analysis. The zone marked by the ellipse falls within a shale-sand sequence of relatively lower porosity. The conventional P-impedance inversion shows that the zone is characterized by a continuous low impedance high porosity sand, which is misleading. However, the P-impedance obtained by the PNN analysis indicates a moderately tight sand which is consistent with the well log signature.

Conclusions

Two case studies from Alberta, Canada are discussed in the article. The case studies involve estimation of P-impedance by model based inversion and neural network analysis. The two approaches are fundamentally different because of their underlying principles. We draw a comparison between the two and show that the estimated P-impedance obtained from PNN analysis and post-stack inversion can be compared within a reasonable accuracy as far as the general low frequency trends are concerned. The results differ in quantitative comparison. The P-impedance estimated by the PNN analysis yields better correlation with the well logs as compared to the P-impedance obtained from the model-based post-stack inversion. The result shows that neural network based analysis yields a solution that is consistent with the well log and hence the local geology. The model based inversion is based on a sound mathematical framework, yet highly susceptible to the selection of the initial model. This is because the inversion is largely affected by the non-uniqueness of the problem.

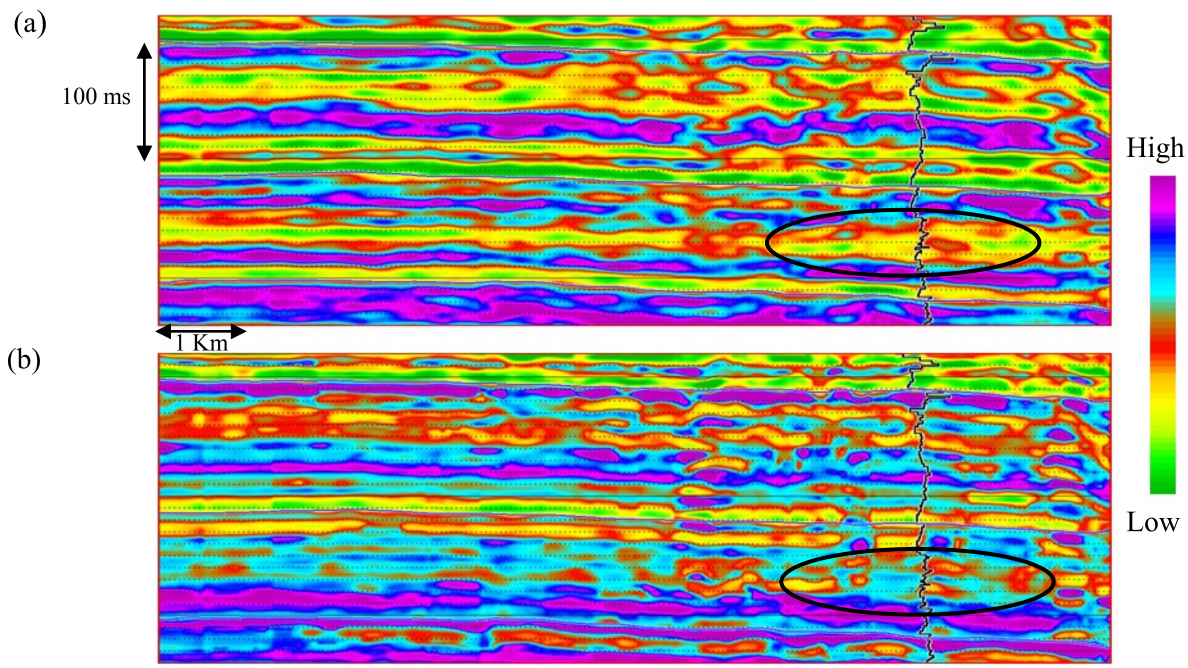

Figure 3: (a) P-impedance obtained from model-based post-stack inversion. (b) P-impedance obtained from PNN analysis. The P-impedance log is inserted. The black ellipse shows the zone of shale-sand play.

Acknowledgements

We acknowledge Arcis Corporation, Canada for the data examples included in this article as well as for the permission to publish it.

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