

Neural network inversion of $\lambda\rho$ and $\mu\rho$ from post-stack seismic attributes

Rongfeng Zhang, Renjun Wen and Donghai Zhuang
Geomodeling Technology Corp.

Summary

$\lambda\rho$ and $\mu\rho$ are the results of pre-stack inversion and they are very popular for seismic interpretation. In areas that AVO effects present, $\lambda\rho$ and $\mu\rho$ are effective parameters to discriminate lithofacies and fluid types. However, $\lambda\rho$ and $\mu\rho$ are not always available in practice for various reasons such as cost, time, data quality, skills etc. We present a new workflow of $\lambda\rho$ and $\mu\rho$ inversion from post-stack attributes and well logs through a neural network approach. The neural network inversion workflow provides an alternative way to obtain $\lambda\rho$ and $\mu\rho$ attribute volumes in areas where pre-stack inversion results are not available. We use the well-known Blackfoot data set in the Western Canada Basin to demonstrate the workflow. The results show that $\lambda\rho$ and $\mu\rho$ derived from post-stack attributes are comparable with those from pre-stack inversion.

Theory and Workflow

Pre-stack inversion gives us P-impedance, S-impedance and density, from which $\lambda\rho$ and $\mu\rho$ can be calculated and used for interpreting reservoir facies and fluid distribution. However, $\lambda\rho$ and $\mu\rho$ are generally not derived from post-stack inversion, which only generates P-impedance. We propose a neural network inversion workflow to predict $\lambda\rho$ and $\mu\rho$ from post-stack attributes and well logs. The workflow consists of five steps:

Step 1: Calculate $\lambda\rho$ and $\mu\rho$ logs from wells that have share sonic and density logs.

Step 2: Build a neural network between $\lambda\rho$, $\mu\rho$ logs and three conventional logs: gamma, compressional sonic, and density. The network is used to predict $\lambda\rho$ and $\mu\rho$ logs in wells that do not have the share sonic log.

Step 3: Upscale $\lambda\rho$ and $\mu\rho$ logs to seismic resolution

Step 4: Build a neural network between upscaled $\lambda\rho$ and $\mu\rho$ logs and seismic attributes along the well path.

Step 5: Apply the neural network built in step 4 to create a seismic stratigraphic grid.

Results

We applied the neural network inversion workflow to the Blackfoot area in Western Canada. There are pre-stack inversion results from the same area (Dufour et al 2002). There are 12 wells

available in the study area. Only four of twelve wells have shear sonic logs (Figure 1). We calculated $\lambda\rho$ and $\mu\rho$ at these four wells from sonic, shear sonic and density logs. The results at well 08-08 are shown in Figure 4 (track 4 and 5). Figure 2 shows a cross-plot between $\lambda\rho$ and $\mu\rho$ at production well 08-08 and regional well 09-17 in the incised valley depth range. The figure shows a good separation. There are three incised valleys in the region, called upper, middle and lower valley respectively. If the depth range is limited to just upper valley, the separation could be even better.

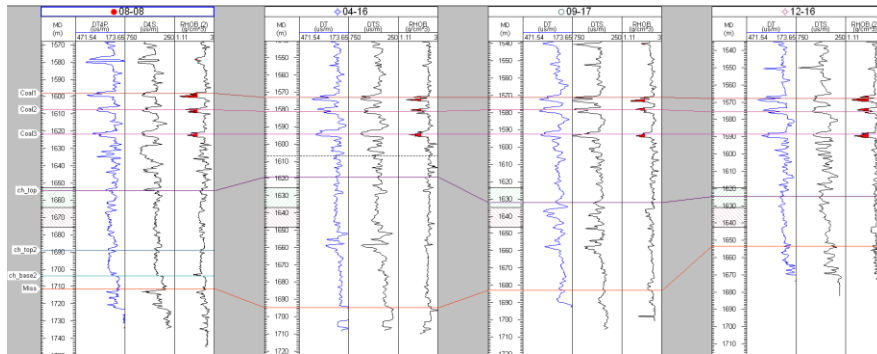


Figure 1 Wells that have shear sonic logs

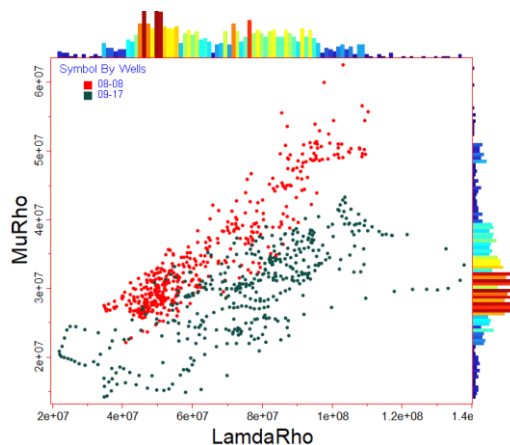


Figure 2 Cross plot between $\lambda\rho$ and $\mu\rho$ at production well 08-08 (red) and regional well 09-17 (blue)

We then train a neural network using data available at four wells that have shear sonic logs. Figure 3 shows cross plots between known $\lambda\rho$ and predicted $\lambda\rho$. Cross plot (labeled as Training) with blue dots shows data points used for training, and cross plot (labeled as Testing) with red dots is for blind test, which means those data points are not used during the training process. An excellent result with correlation 0.97 is achieved. Then the predictions on each well are made. Figure 4 shows the predicted $\lambda\rho$ and $\mu\rho$. From well 08-08 we can evaluate how good the predicted $\lambda\rho$ (track 6) and $\mu\rho$ (track 7) comparing to the actual logs (track 4 and 5). In this example, the results are quite good, though some slight amplitude differences exist. Well 01-08 doesn't have shear sonic logs, so only the predicted results are displayed on track 4 and 5.

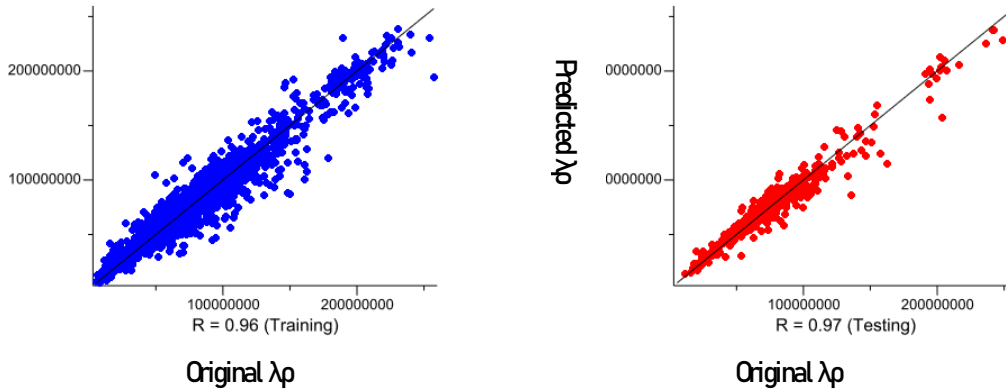


Figure 3 Cross plots from neural network training for λ_p log prediction at wells

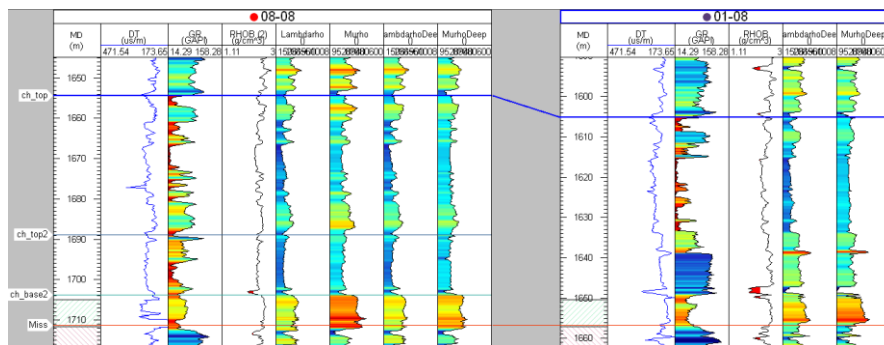


Figure 4 Compare λ_p and μ_p between the predicted (track 4 and 5) and the calculated (track 6 and 7)

Once λ_p and μ_p at every well in the region are predicted, they are upscaled in the interest zone according to seismic resolution. The results are shown in Figure 5. Then, another neural network is trained between the seismic attributes (26 in total) at each well location and λ_p or μ_p . A correlation coefficient of 0.75 overall is achieved. λ_p and μ_p volumes are subsequently predicted using the trained neural network. A map view of λ_p from the upper valley interval is shown in Figure 6 where area with lower λ_p value within the incised valley system corresponds to gas sand zone. They match the results from pre-stack inversion quite well.

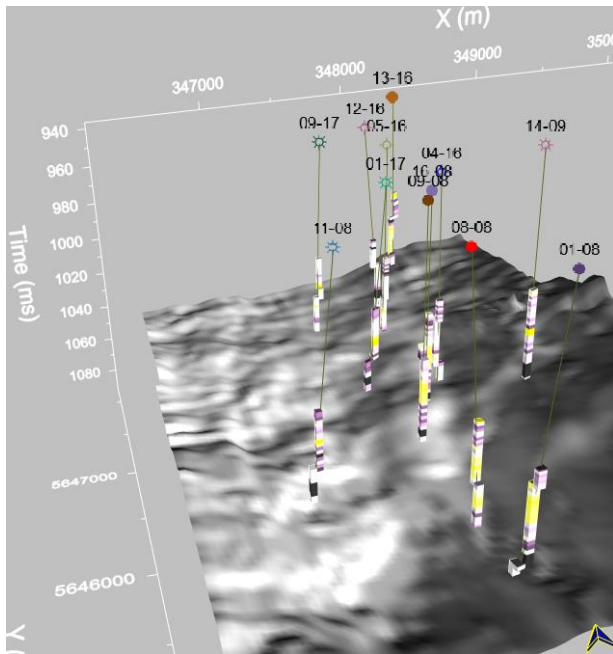


Figure 5 Upscaled $\lambda\rho$ and $\mu\rho$ at each well

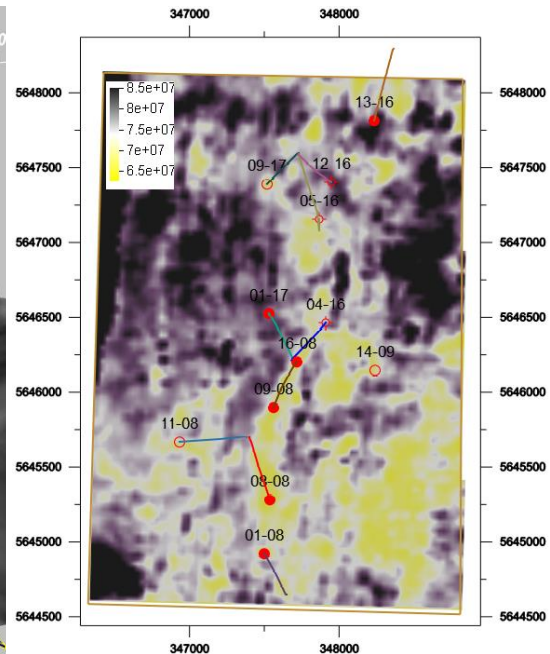


Figure 6 Map view of predicted $\lambda\rho$ in the upper valley interval

Acknowledgements

We thank Geomodeling Technology Corp. for both technique and financial support.

References

1. AVO and Lamé' constants for rock parameterization and fluid detection, Goodway W. Recorder 2001, 26, 39-60.
2. Integrated geological and geophysical interpretation case study, and Lamé rock parameter extractions using AVO analysis on the Blackfoot 3C-3D seismic data, southern Alberta, Canada, Jocelyn Dufour, Jason Squires, William N. Goodway, Andy Edmunds, and Ian Shook
GEOPHYSICS 2002 67:1, 27-37