Self Organizing Maps Applied to Seismic Attributes as a Tool to Improve Stratigraphic Resolution

Carolan Laudon, Rocky Roden, Thomas Smith, Sarah Stanley, Patricia Santogrossi, Robert Hardage*
Geophysical Insights

Introduction

Over the last few years, because of the increase in low cost computer power, individuals and companies have stepped up investigations into the use of machine learning in many areas of E&P. For the geosciences, the emphasis has been in reservoir characterization, seismic data processing and to a lesser extent, interpretation. The benefits of using machine learning (whether supervised or unsupervised) has been demonstrated throughout the literature and yet the technology is still not a standard workflow for most seismic interpreters.

This lack of uptake can be attributed to several factors including: a lack of software tools, clear and well-defined case histories and training. Fortunately, all these factors are being mitigated as the technology matures. Rather than looking at machine learning as an adjunct to the traditional interpretation methodology, both supervised and unsupervised machine learning techniques should be on the front end of the interpretation workflow.

Workflow

By using statistical tools such as Principal Component Analysis (PCA) and Self Organizing Maps (SOM) a multi-attribute 3D seismic volume can be “classified”. The PCA reduces a large set of seismic attributes both instantaneous and geometric, to those that are the most meaningful. The output of the PCA serves as the input to the SOM, a form of unsupervised neural network, which when combined with a 2D color map facilitates the identification of clustering within the data volume. When the correct “recipe” is selected the clustered or classified volume allows the interpreter to view and separate geological and geophysical features that are not observable in traditional seismic amplitude volumes. Seismic facies, detailed stratigraphy, direct hydrocarbon indicators, faulting trends, and thin beds are all features that can be enhanced by using a classified volume.

Examples of Thin Bed Resolution below Tuning

The tuning-bed thickness or vertical resolution of seismic data traditionally is based on the frequency content of the data and the associated wavelet. Seismic interpretation of thin beds routinely involves estimation of tuning thickness and the subsequent scaling of amplitude or inversion information below tuning. These traditional below-tuning-thickness estimation approaches have limitations and require assumptions that limit accuracy. The below tuning effects are a result of the interference of wavelets, which are a function of the geology as it changes vertically and laterally. However, numerous instantaneous attributes exhibit effects at and below tuning, but these are seldom incorporated in thin-bed analyses. A seismic multi-attribute approach employs self-organizing maps to identify natural clusters from combinations of attributes that exhibit below-tuning effects. These results can exhibit changes as thin as a single sample interval in thickness. Self-organizing maps employed in this fashion analyze associated seismic attributes on a sample-by-sample basis and identify the natural patterns or clusters produced by thin beds.

Examples of this approach to improve stratigraphic resolution will be demonstrated with cases from the Niobrara Formation of the Denver-Julesburg Basin (Figure 1) and the Eagle Ford of South Texas and with a multi-component case which reveals karsting in the Ellenburger in East Texas.

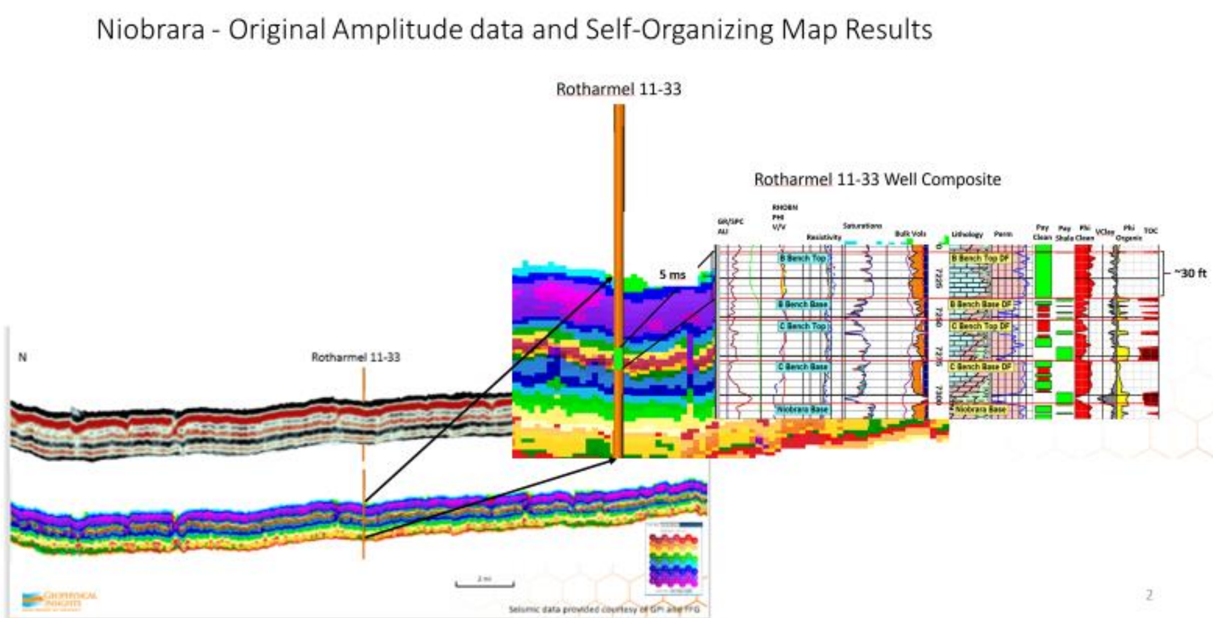

Figure 1 Comparison of original amplitude data with a 64 neuron self-organizing map based on 8 instantaneous attributes. The well composite highlights the tie between the SOM neurons and the B Chalk Bench which is resolved to 5 milliseconds. The red-brown neurons within the bench correlate to the maximum carbonate content and best pay within the reservoir.

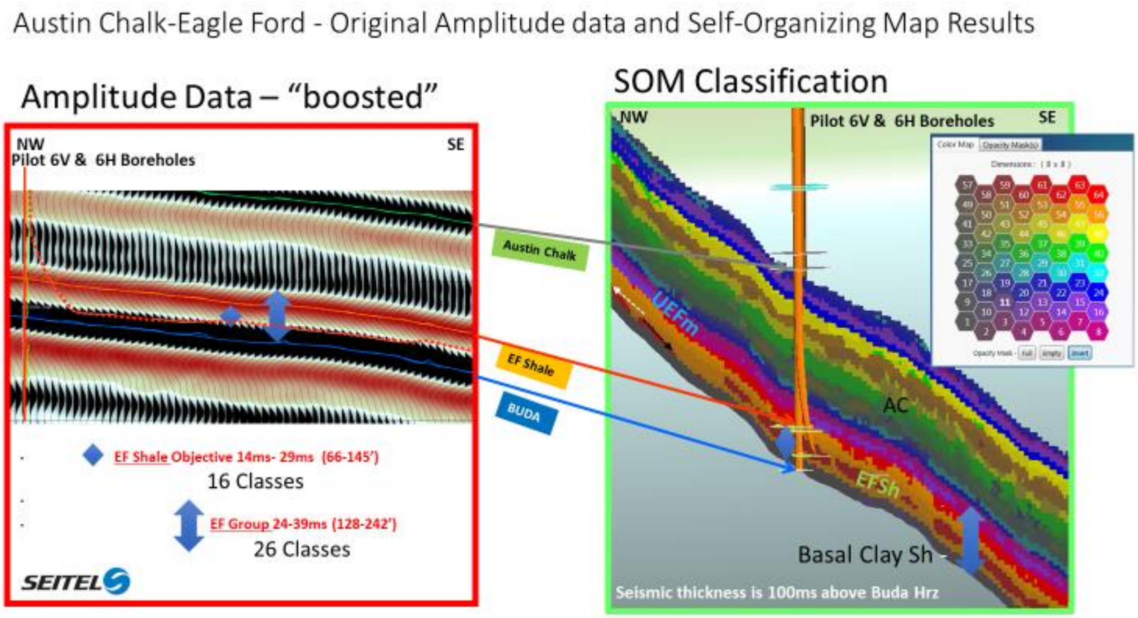

Figure 2 Comparison of original amplitude data with a 64 neuron SOM result based on 10 instantaneous attributes. The Lower Eagle Ford is represented by 16 distinct neuron classes and beds as thin as 5 feet were detected.

Acknowledgements

3D seismic data is presented with permission from Geophysical Pursuit, Inc. and Fairfield Geotechnologies for the Niobrara and Seitel for the Austin Chalk-Eagle Ford.

References

Coleou, T., M. Poupon, and A. Kostia, 2003, Unsupervised seismic facies classification: A review and comparison of techniques and implementation: The Leading Edge, 22, 942–953, doi: 10.1190/1.1623635.

Guo, H., K. J. Marfurt, and J. Liu, 2009, Principal component spectral analysis: Geophysics, 74, no. 4, p. 35–43.

Haykin, S., 2009, Neural networks and learning machines, 3rd ed.: Pearson.

Kohonen, T., 2001, Self organizing maps: Third extended addition, Springer, Series in Information Services, Vol. 30.

Laudon, C., Stanley, S., and Santogrossi, P., 2019, Machine Learning Applied to 3D Seismic Data from the Denver-Julesburg Basin Improves Stratigraphic Resolution in the Niobrara, **https://doi.org/10.15530/urtec-2019-337**

Roden, R., and Santogrossi, P., 2017, Significant Advancements in Seismic Reservoir Characterization with Machine Learning, The First, v. 3, p. 14-19.

Roden, R., Smith, T., and Sacrey, D., 2015, Geologic pattern recognition from seismic attributes: Principal component analysis and self-organizing maps, Interpretation, Vol. 3, No. 4, p. SAE59-SAE83.

Santogrossi, P., 2017, Classification/Corroboration of Facies Architecture in the Eagle Ford Group: A Case Study in Thin Bed Resolution, URTeC 2696775, doi 10.15530-urtec-2017-<2696775>.