A neural networks based seismic object detection technique

Fred Aminzadeh[1], Paul deGroot[2];
[1] dGB-USA, One Sugar Creek Center Blvd., Suite 935, Sugar Land, TX, 77478,
[2] dGB Earth Sciences, 7511 JM Enschede, The Netherlands, info.usa@dgb-group.com

Summary

Seismic technology has historically focused on resolving the structures. To a lesser degree, presence or absence of reservoir has also been a focus. This paper shows the use of seismic data to detect several other "seismic objects". The technique to be referred to as "meta attribute", uses the combination of "artificial intelligence" of neural networks and the "natural intelligence" of an interpreter. Examples of many geologic features and reservoir properties detected using this technique will be provided. They include hydrocarbon probability, lithofacies, chimney, faults and salt.

Introduction

The advent of 3D and 4D technology and increasing computing power have led to an explosion in application of seismic attributes. Seismic attributes were first "clustered" or combined by Aminzadeh and Chatterjee (1985). This was accomplished by first, performing a "principal component analysis" (PCA), ensuring they are not correlated. This was followed by "clustering" to highlight gas related bright spots using several attributes in the factor space. Clustering or other conventional statistical tools (regression, cross plots, etc) allow a linear transformation to combine different attributes and compare their respective contribution and role in the classification process. Nowadays there is an increasing need to identify subsets or combinations of attributes that can highlight a given geological or reservoir property most effectively.

Rapid expansion of the number of attributes to be evaluated and the enormous size of multiple volumes of various attributes started to become unwieldy. One solution to this problem was offered by de Groot and Bril (1997). They maintain that since all seismic attributes are derived from the original seismic wavelet response, the original wavelet should include all the information content of all derived attributes. "Seismic character" can be combined with certain attributes to exaggerate subtle features. For example, the frequency attribute may be a good sand indicator but for very thin sand, square of frequency may be needed to highlight sand bodies. Also, spatial information (e.g. cube similarity or azimuth variance) and pre stack seismic information (e, g, AVO) can be captured by defining new attributes.

Why neural networks and meta Attribute?

Several different neural network-based methods to handle and better utilize seismic attributes have been introduced, e.g. Schuelke et al, 1997 and Aminzadeh and de Groot, 2004. Neural network-based methods, has many advantages. Among them are their noise tolerance and their ability to fully capture and account for the non-linear relationship between the seismic data and reservoir properties, as well as nonlinear transformation of seismic attributes

The mechanism to combine different attributes, such as regression analysis, principal component analysis, clustering or neural networks assist in the overwhelming task of evaluating and visualizing the impact of different attributes on the output. However, these methods on their own can be considered a black box. Usually there is no possibility to incorporate the knowledge and insight of the interpreter in conventional clustering or neural network approaches. Meldahl et al (2001) and Rooij and Tingdahl (2002) introduced a method that forms the basis for the meta- attribute approach. One aspect of the "meta attribute" concept is its versatility in the training process. The following are the main features of meta-attributes:

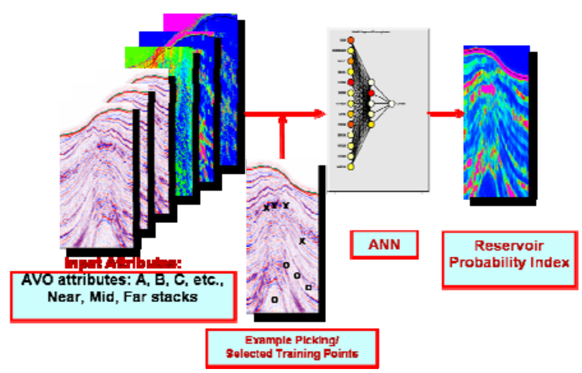

Figure 1, Meta- Attribute Concept combining Human and Machine Intelligence

Figures 1 shows the procedure, which is similar to a conventional neural network-based method with the important addition of the "Example Picking/Selected Training Points" box For example let us assume the focus of the interpretation work is to highlight all the areas with high probability of hydrocarbon. The first step is to examine the data set and identify areas to be known (from well entries) or suspected hydrocarbons (with visual inspection geologic interpretation of the data.). Such points are identified as (1) Using the same concept, we also identify representative areas, which are likely to be "no-hydrocarbon". Those points are shown by (o).

After attribute calculations and going through the training, testing and application phase, we can then create an implicit non-linear transformation of all the attributes that we can call "Hydrocarbon Attribute" In an ideal situation, Hydrocarbon Attribute should highlight only those areas within the 3-D volume that correspond to areas with large probability of having hydrocarbon and nothing elsewhere (based on a user defined threshold). Practically, we create a "Hydrocarbon Probability Attribute" or HPA volume with large values of HPA associated with those areas that have closer overall "likeness" to the combination of attributes represented by the "known" or interpreted hydrocarbon.

Examples of Meta Attributes:

Meta Attributes are used to highlight any seismic anomaly that can be related to a particular geological or reservoir property seismically. This includes a large number of post stack and pre-stack attributes. Time lapse (4D) data and multi-component (4C) data could also be used as input. Aside from the HPA discussed earlier, among features that have been detected using meta attributes are salt bodies, chimneys, faults, lithologies (channel and sheet sand, shale and levees,) Tuning thickness (through spectral decomposition,) fractures, reefs, and 4D anomalies.

In what follows, we will provide examples on a selected number of geologic and seismic objects that have been highlighted through this approach.

Hydrocarbon Probability Meta-Attribute

Figure 2 shows a section through a hydrocarbon probability volume, using the concept described earlier. The training is based on geologist interpretation and information from a number of known wells. The input to the neural network include absorption related attributes (measure of high frequency loss due to transmission of seismic waves through columns of hydrocarbon saturated rocks) as well as angle gather data indicating variation of amplitude and other attributes with offset. The events highlighted in green and blue show areas with higher probability of hydrocarbon, some confirmed by wells (one shown). The vertical black and gray events are "gas chimney" events, to be described later, also show good correlation with those events highlighted as high probability of hydrocarbon.

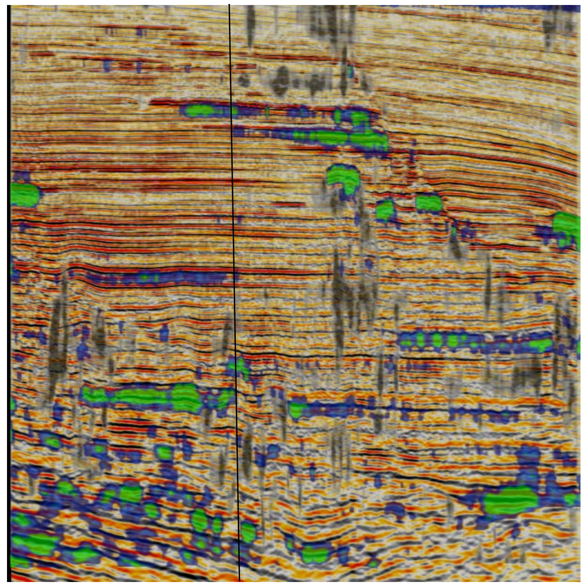

Figure 2- A Hydrocarbon Probability Meta Attribute

Salt Meta Attribute

In Figure 3 we show how a salt body is isolated, based on the meta-attribute concept. The procedure described earlier on HPA is modified by selecting the "salt" and "non-salt" seed points on the original seismic data and training the neural network accordingly. Naturally, a somewhat different set of input attributes are used to make the distinction in this case.

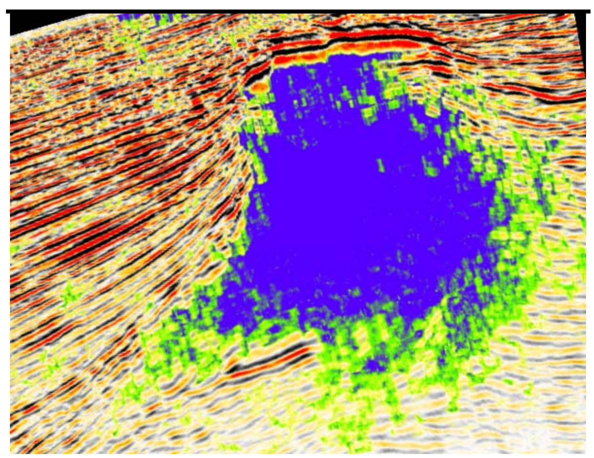

Figure 3- A Salt Meta Attribute.

Areas highlighted in blue, green and yellow indicate high, medium and low "likeness" to salt features picked by the interpreter in the training process.

Chimney Meta Attribute

As it was described in Meldahl et al (2001) and Connolly and Aminzadeh 2003) gas chimneys can be used not only for geohazard detection but also as an effective exploration tool. Through focusing on the vertical chaotic seismic disturbance in 3-D data we create a chimney meta-attribute volume that highlights fluid migration pathways. It can also help determine the seal integrity and charge capacity. Thus combined with other meta-attributes and other data chimney volumes can be used as a useful tool to gain a better understanding of the petroleum system and serve as an indicator for hydrocarbon migration and entrapment. Figure 4 shows a “Chimney meta-attribute” overlain on a conventional seismic section.

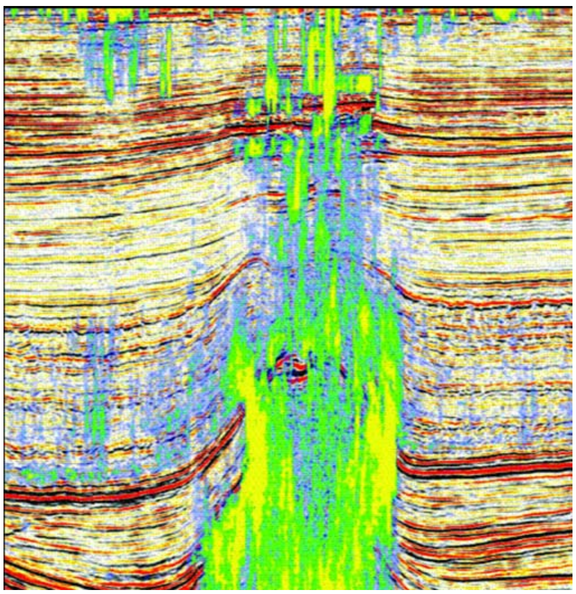

Figure 4- A Chimney Meta Attribute

Fault Meta Attribute

Using a similar approach, but through picking known or suspected faults we highlight both obvious and subtle faults. Figure 6 (bottom panel) shows one such result with a few slices of fault volumes and a slice of the original seismic data. In our experience faults highlighted by this method are more continuous than faults identified by the conventional similarity- or coherency-based approaches. Factors contributing to the success of a fault cube are: a) the input attributes are “dip-steered”, meaning that the attribute response is calculated along the seismic reflection energy that forms geologic horizons. b) the input to the neural network comprises many attributes, including similarity, each of which may respond to different types of faults differently. c) Interpreter’s insight is incorporated in the process in the form of handpicked fault and non-fault positions. Figure 5 shows Improvement gained from the use of meta-attributes in highlighting more subtle faults are evident when the results of fault cube are compared against the conventional similarity (coherency),

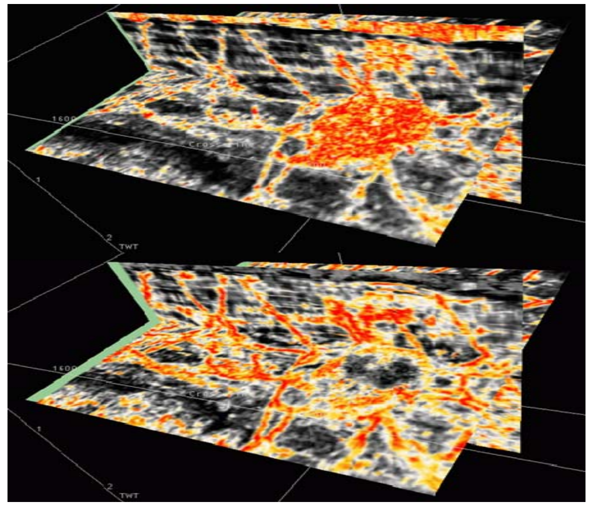

Figure 5, Comparison of Fault Meta Attribute (bottom) and conventional similarity (top)

Lithology Meta Attribute

Figure 6 shows an example of the lithology meta-attribute. In this case, instead of creating a “two-class” output such as salt versus no salt or fault/no fault, we create a three-class output, comprised of channel, levee and silt-shale with their respective confidence levels. Here, while the colors show different lithology classes, the brightness shows the associated confidence in the classification process.

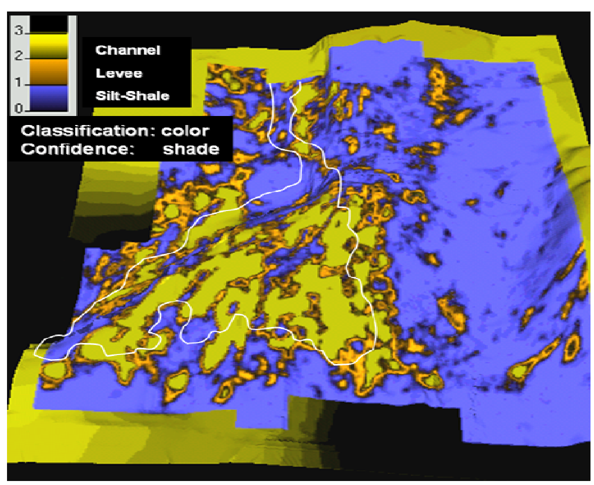

Figure 7, A three-class lithology Meta Attribute

Spectral Decomposition Attribute

Spectral Decomposition (SD) is another attribute that either by itself or in conjunction with other attributes can improve "below resolution" seismic interpretation, sand thickness estimation and highlighting channels. In SD spectral properties, or scale properties are extracted from a small part of the reflectivity series through mathematical transformation. As a consequence of the small transform window the spectral response of the geological column is not "white" but contains effects such as spectral notches and tuning frequencies that relate to the local reflectivity only, hence geological properties such as stratigraphic units, layer thickness and stacking patterns are highlighted. Combining spectral slices we can see subtle features, often below seismic resolution, which are not as clear on the single attribute section such as energy or instantaneous frequency.

In Figure 8, amplitude and energy attributes are contrasted against the three spectral bands. Different areas brighten up at different frequencies to highlight the main meandering, indicating variations of thickness within the channel (good connectivity), or channels composed of sedimentary sub-bodies, some of which may be deposited during catastrophic event like flooding (poor connectivity)

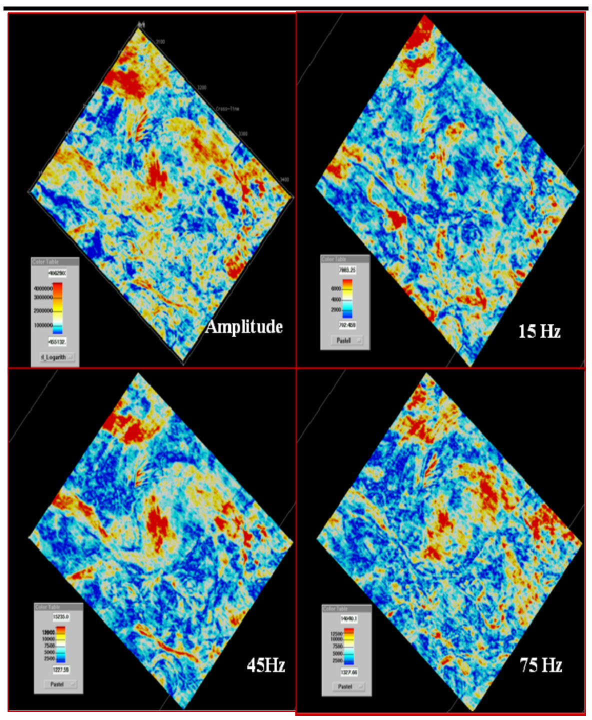

Figure 8, A horizon slice of the original seismic and different spectral bands.

Conclusions

The neural networks based meta-attributes that incorporate interpreter's knowledge have many advantages for creating outputs with desired seismic objects associated with particular geologic features and/or reservoir properties. Aside from the ability to combine different attributes to benefit from their respective prediction power, they allow interaction of the interpreters with the neural network during its training process. Thus their intuition and expertise can complement the strength of different attributes and help better training of the neural network.

This method can be used for detecting any geologic feature or reservoir property whose foot print can be traced to a particular change in the seismic response. Among geologic features detected, are: salt, gas chimney, fault, fracture, sand thickness, lithology, hydrocarbon probability and dynamic changes in the reservoir highlighted by the time-lapse data.

References

Aminzadeh, F., de Groot, P.., 2004, Soft Computing for qualitative and quantitative seismic object and reservoir property prediction, Part 1, Neural network applications, First Break, Volume 22, pp 49-54.

Aminzadeh, F., and Chatterjee, S., 1984. Applications of Cluster analysis in Exploration Seismology, Geoexploration, Vol. 23, pp. 147-159,

Berge, T.B., F. Aminzadeh, P. de Groot, T. Oldenziel, 2002. Seismic Inversion Successfully Predicts Reservoir Porosity, and Gas Content in Ibhubesi Field, Orange Basin, South Africa: The Leading Edge, 21, no. 4, 338-348.

Connolly, D. L. and Aminzadeh, F. 2003, Geo-Hazard Detection with Chimney Cubes, Offshore Technology Conference Paper # 15114.

de Groot, P. F. M. and Bril, A. H., 1997. Quantitative interpretation generally needs no seismic attributes, 59th Mtg.: Eur. Assn. Geosci. Eng., Session:E018.E018.de Rooij, M. and Tingdahl, K. , 2002. Meta-attributes- The key to multi-volume, multi-attribute interpretation, The Leading Edge, 21, no. 4, 1050-1053.

Meldahl, P., Heggland, R., Bril, B., and de Groot, P., 2001. Identifying Fault and Gas Chimneys Using Multi-Attributes and Neural Networks, The Leading Edge of Geophysics, pp. 474-482.

Schuelke, J. S., Quirein, J. A., Sarg, J. F., Altany, D. A. and Hunt, P. E., 1997. Reservoir architecture and porosity distribution, Pegasus field, West Texas -- an integrated sequence stratigraphic -- seismic attribute study using neural networks, 67th Ann. Internat. Mtg: Soc. of Expl. Geophys., 668-671