

META ATTRIBUTES: A NEW CONCEPT DETECTING GEOLOGIC FEATURES & PREDICTING RESERVOIR PROPERTIES

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Abstract

Detecting geologic features such as faults, salt, sand channels, and gas chimneys as well as predicting reservoir properties such as sand thickness, lithology and hydrocarbon probability are the focus of this paper. These can be accomplished using a new technique that combines seismic attributes in a special way. We search through different data volumes looking for specific types of anomalous seismic response using criteria referred to as "meta-attributes." Meta-attributes are an aggregation of a number of seismic attributes combined with the interpreter's insight through a neural network to detect a particular feature. One of the main features of the meta-attribute concept is combining "artificial intelligence" of neural networks with the "natural intelligence" of an interpreter. This leads to a more comprehensive integration of geological, petrophysical and seismic data. Non-linear interrelationships between data as well as knowledge versus geologic features and reservoir properties are defined implicitly at the natural scale. Meta attributes extracted from multiple input seismic volumes and derived attributes are used to predict facies, lithology and hydrocarbon probability, as well as for detecting faults, fractures, channels, gas chimneys or salt bodies. The meta-attribute approach is placed in the historical context, the technology is explained and examples for various seismic object detections problems are given.

How Attribute Technology Have Evolved

Seismic attribute technology has been gaining popularity ever since it was introduced by Taner et al (1979). These originally introduced "instantaneous attributes" and the subsequent multi-trace and pre-stack attributes have found many applications in different exploration and field development problems. Figure 1 shows the evolution of attribute technology during the last four decades. The text to the right of the road shows the actual applications and those to the left, the corresponding technologies. In recent years the advent of 3D and 4D technology and increasing computing power led to an explosion in useful attributes. Nowadays there is an increasing need to identify subsets or combinations of attributes that can highlight a given geological or reservoir property most effectively.

The first publication in which several attributes were combined for E&P applications was by Aminzadeh and Chatterjee (1985). This was accomplished by first, performing a "principal component analysis" (PCA) to transform the attributes to the "factor space", 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,



Figure 1, Evolution of Attribute Technology

etc.) allow a linear transformation to combine different attributes and compare their respective contribution and role in the classification process. Subsequently, it was suggested by, for example, Wong et al (2003), that in many circumstances, unconventional statistical methods may be required to fully capture and account for the non-linear relationship between the seismic data and reservoir properties. Neural network-based methods, offer one such possibility, allowing non-linear transformation of attributes to establish stronger and more accurate relationship between the seismic data (seismic attributes) and the geological features or reservoir properties (Schuelke et al, 1997 and Aminzadeh and de Groot, 2004).

Meta Attributes Methodology?

The 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 Brill (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. Thus, "seismic character" analysis should be able to replace attributes for quantitative interpretation.

While this argument is valid in most cases, there are many situations where attribute analysis, perhaps in conjunction with "seismic character" represented by a windowed seismic response, would be desirable. Contribution of certain attributes may need to be exaggerated to highlight 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.

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:

- Pre-processing through steering and filtering
- Combining attributes
- Nonlinear mapping of attributes via use of neural network
- Ability to use Interpreter’s knowledge
- Zero in on a specific object

Figures 2 and 4 show the procedure, which is similar to a conventional neural network- based method with the important addition of the “Example Picking/Selected Training Points” box in Figure 2 and the “Interpreter’s Knowledge” box in Figure 4. For example let us assume the focus of the interpretation work is to highlight all the areas with high probability of hydrocarbon in an area within a given 3-D seismic survey. The first step is to examine the data set and identify areas to be known (from well entries) or suspected salt (with visual inspection geologic interpretation of the data.). Such points are identified as (1) in Fig. 2. Using the same concept, we also identify representative areas, which are likely to be “no-hydrocarbon”. Those points are shown by (o) in Figure 2.

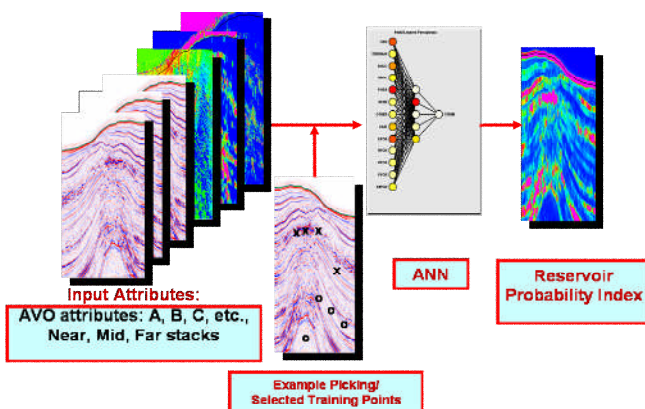


Figure 2, Meta- Attribute Concept combining Human and Machine Intelligence

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, 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.

A- Hydrocarbon Probability Meta-Attribute

Figure 3 shows a slice of 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.

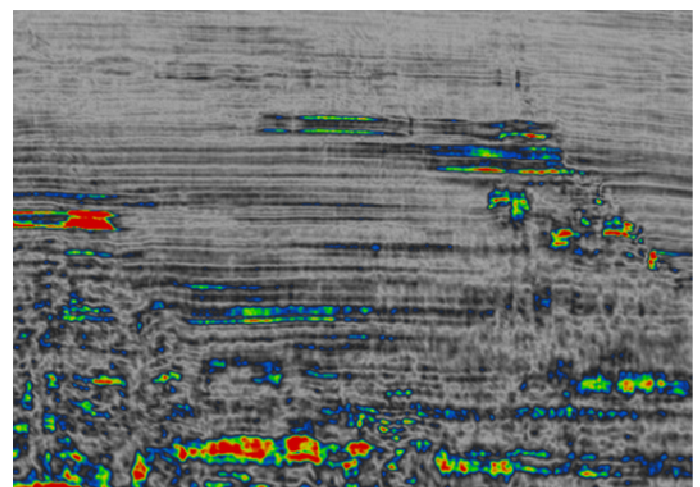


Figure 3- A Hydrocarbon Probability Meta Attribute B- Salt Meta Attribute

In Figure 4 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.

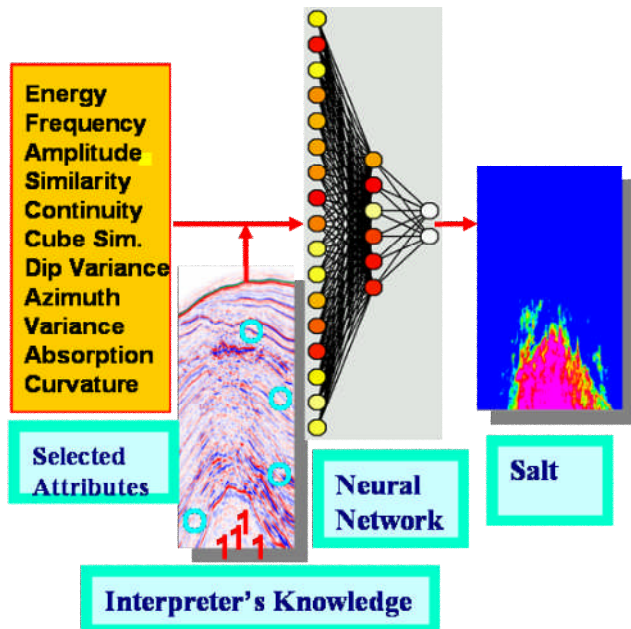


Figure 4, Calculation of “Salt Meta Attribute”

C- 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 attributes 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 5 shows a “Chimney meta attribute” overlain on a conventional seismic section.

many different types of attributes, including similarity, each of which may respond to different types of faults differently. Thirdly, interpreter’s insight is incorporated in

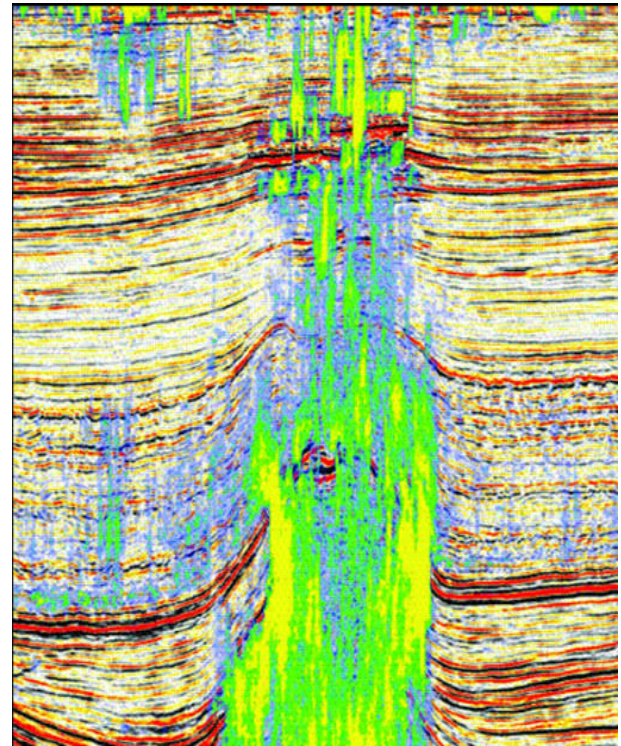


Figure 5- A Chimney Meta Attribute

D- 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. The following factors contribute to the success of a fault cube:

Firstly, the input attributes are “dip-steered”, meaning that the attribute response is calculated along the seismic reflection energy that forms geologic horizons. Secondly, the input to the neural network comprises

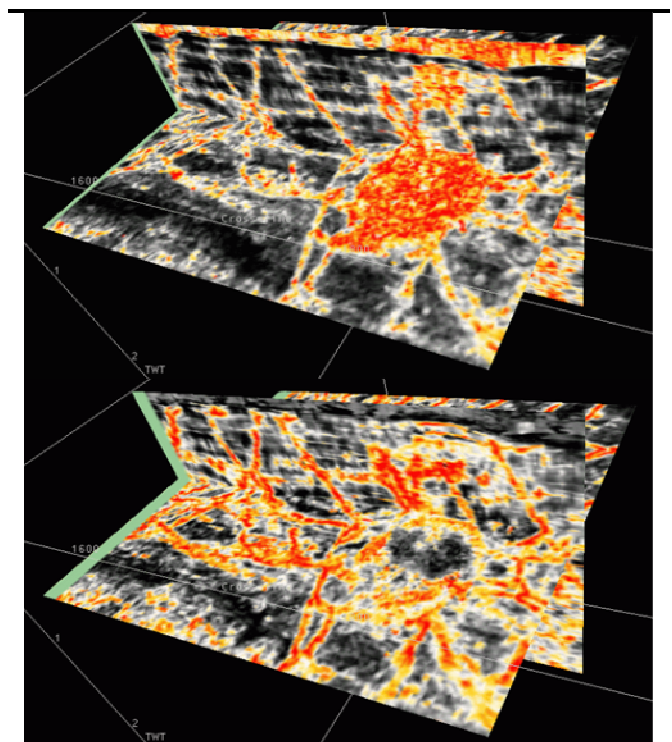


Figure 6, Comparison of Fault Meta Attribute (bottom) and the conventional Similarity (top) the process in the form of handpicked fault and non-fault positions. Improvement gained from the use of meta-

attributes in highlighting more subtle faults are evident when the results of fault cube in Figure 6 the fault meta attribute (the bottom panel) is compared against the conventional similarity (coherency) based method output (top panel).

E- Lithology Meta Attribute

Figure 7 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.

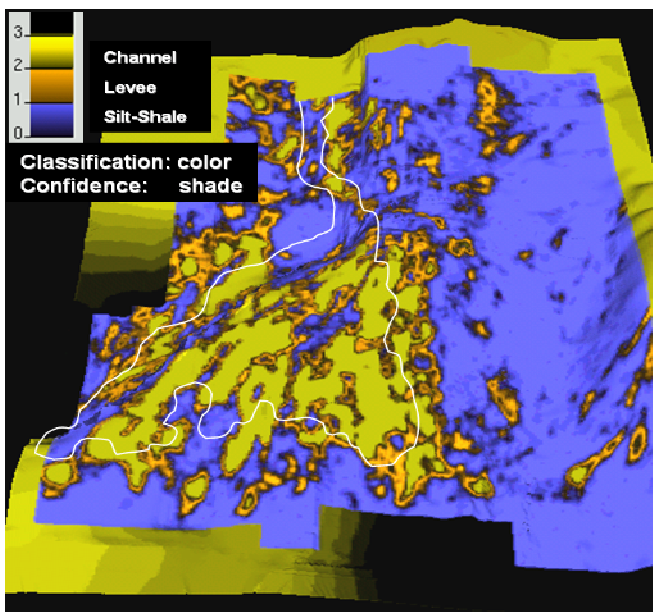


Figure 7, A three-class lithology Meta Attribute

F- 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, amplitude or instantaneous frequency. In Figure 8, amplitude and energy attributes are contrasted against the three spectral bands.

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)

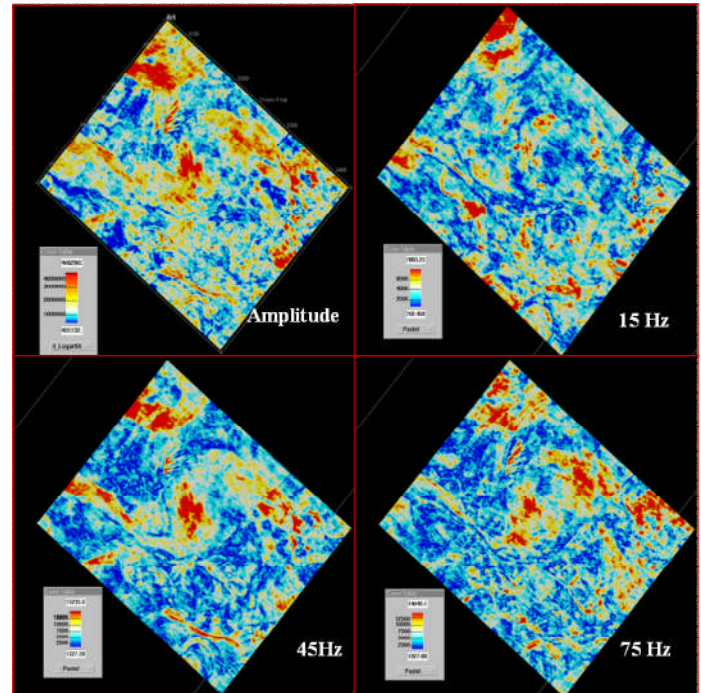


Figure 8, A horizon slice of the original seismic and different spectral bands.

Conclusions

The newly introduced meta-attribute has 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.

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