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Interactive multi-volume seismic attribute analysis in OpendTect

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Seismic attributes are powerful instruments for data visualization and integration. In this article examples are shown of multi-volume seismic attribute analysis using OpendTect, a software system that is released under a unique open source licensing scheme. We start with a general introduction to OpendTect and its capabilities. We then discuss meta-attributes, which are intelligent combinations of multiple attributes to highlight features of interest in the seismic data. Next we show examples of neural network-based attribute analysis such as TheChimneyCube®, seismic facies analysis and rock property prediction.

OpendTect

OpendTect is an open source seismic interpretation environment for processing, visualizing and interpreting multi-volume seismic data, and for fast-track development of innovative interpretation tools. OpendTect Base, the open source part, is free for R&D, education and evaluation purposes. Commercial users pay a modest maintenance fee. The main features in OpendTect Base are:

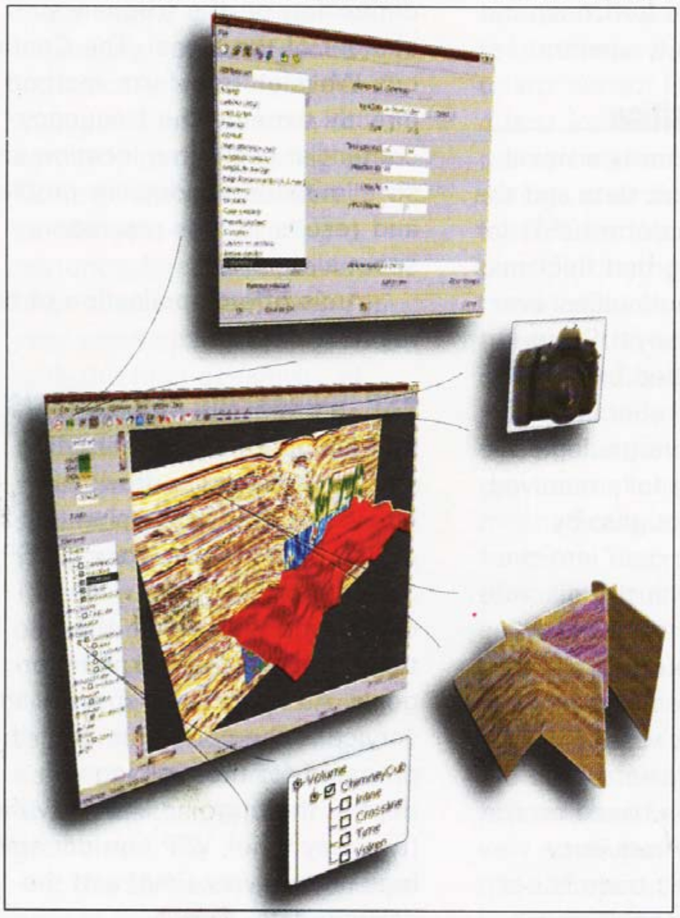

Figure 1: OpendTect impression.

- On-the-fly calculation and visualization of both unique and commonly used filters and attributes
- Mathematical and logical expressions to create your own attributes and filters (incl. attributes from attributes)
- Movie-style parameter testing
- Volume-rendering and stereo-viewing
- Semi automatic horizon-tracking
- Spectral decomposition with Fourier Transforms & Continuous Wavelet Transforms
- Multi-platform distributed computing
- Plugin architecture
- Data I/O via SEG-Y and ASCII
- Mixed 2D and 3D seismic data compatibility
- C++ source code with examples and documentation

The software is currently supported on PC-Linux, Sun-Solaris, SGI-Irix, Mac-OS/X and MS-Windows (2000/NT/XP). Heavy processing of large volumes can be carried out in batch mode on multiple machines. Any combination of platforms and machines (single- or multi-processor machines in heterogeneous networks or clusters) can be used for this purpose. Figure 1 gives an impression of the OpendTect user interface.

OpendTect can be extended at run-time for added functionality with the following commercial plugins:

- Dip-steering
- Neural networks
- Workstation access to and from

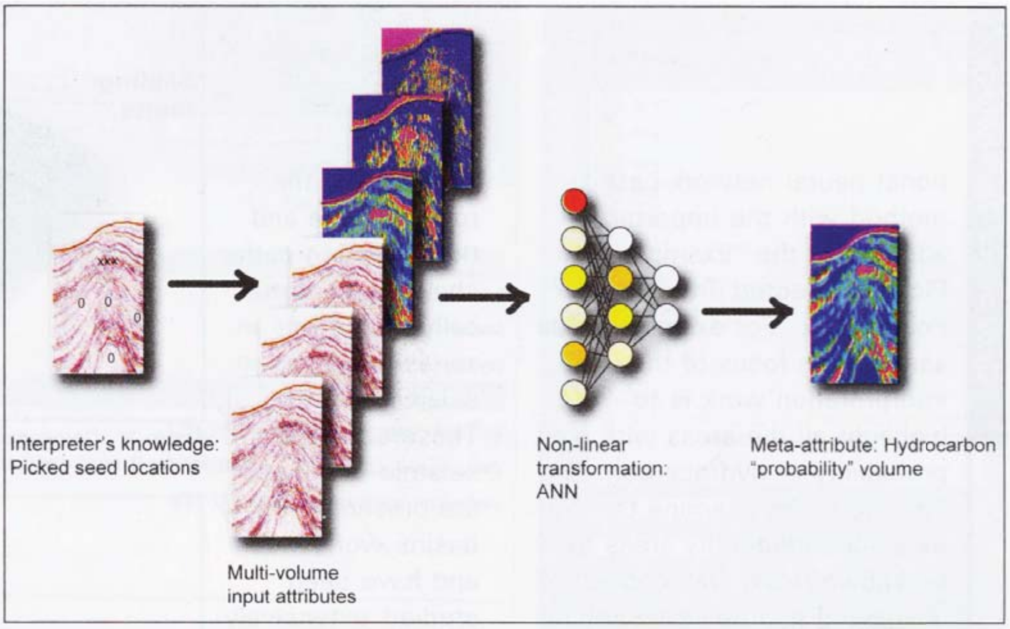

Figure 2: Meta- Attribute Concept combining Human and Machine Intelligence.

SeisWorks and GeoFrame-IESX

The dip-steering plugin allows you to create and use steering cubes that contain local dip and azimuth information of seismic events at every sample location. The cube is essential for structure-oriented filtering, and improves resolution of numerous multi-trace attributes by honoring and following dipping reflectors. It also features unique attributes like curvature in a 3D volume, eliminating the need to pick horizons first.

The Neural Network plugin supports supervised and unsupervised neural networks to combine multiple attributes into "meta-attributes." Meta-attribute analysis eliminates the need to look at numerous different attributes simultaneously (for details see the following Section). The main application of unsupervised networks is clustering of attributes and/or waveforms for seismic facies analysis. The supervised approach is used for more advanced seismic facies analysis and to create object "probability" cubes such as TheChimneyCube® and TheFaultCube®.

The Workstation data access module is based on the Ideal toolkit from ARK CLS. It supports direct import and export of seismic volumes, horizons and well data to and from Landmark's SeisWorks/OpenWorks and Schlumberger's GeoFrame-IESX workstations.

Meta-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.

Figures 2 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 (by visual inspection and geologic interpretation of the data.). Such points are identified as (X) in figure 2. 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 the "Hydrocarbon Attribute". In an ideal situation, the 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 locations.

The Chimney Cube

When hydrocarbons migrate through the sub-surface rocks may crack or are chemically altered while gas might be released when the pressure drops and might get trapped in the pores of the migration path. As a result the seismic response of the rocks change and the migration paths show up as vertically disturbed zones in the seismic record. These so-called seismic chimneys are present in many basins worldwide and have been studied extensively since the arrival of the chimney cube in 1998. A chimney cube is created from multiple attributes by training a neural network on manually picked examples of chimneys and non-chimneys as described above. Highlighting these fluid migration pathways provides a better insight in the spatial relationship between the various elements of the petroleum system. These include processes such as:

- Fluid activity in source rocks that may be related to active hydrocarbon expulsion.
- Gas chimneys and fluids migrating along faults and reaching potential reservoir formations, thereby providing information about whether a prospect is charged or not.
- Leakage from potential reservoirs, which may provide better insight in the lateral and top seal quality.
- Leakage from these potential reservoirs to shallower levels and charging shallow sands, thus indicating the presence of shallow gas drilling hazards.
- Hydrocarbons reaching the seabed, creating mud volcanoes and pockmarks; the occurrence of such features is important, as they influence the positioning of new offshore installations and pipelines .

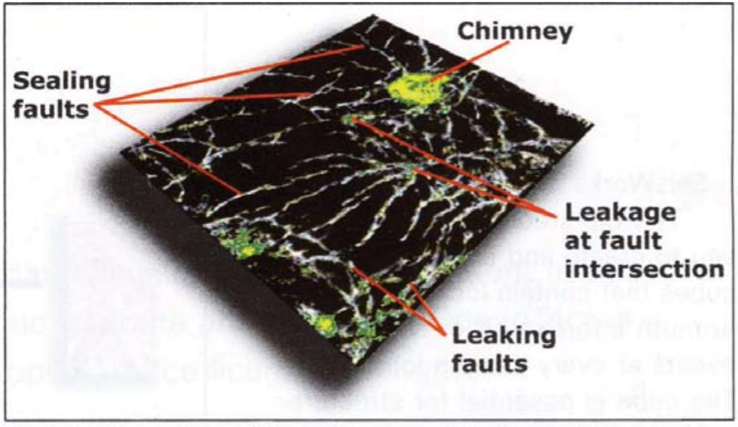

Figure 3: Comparison of time-slices through fault and chimney cubes for fault seal analysis. From Ligtenberg (2005).

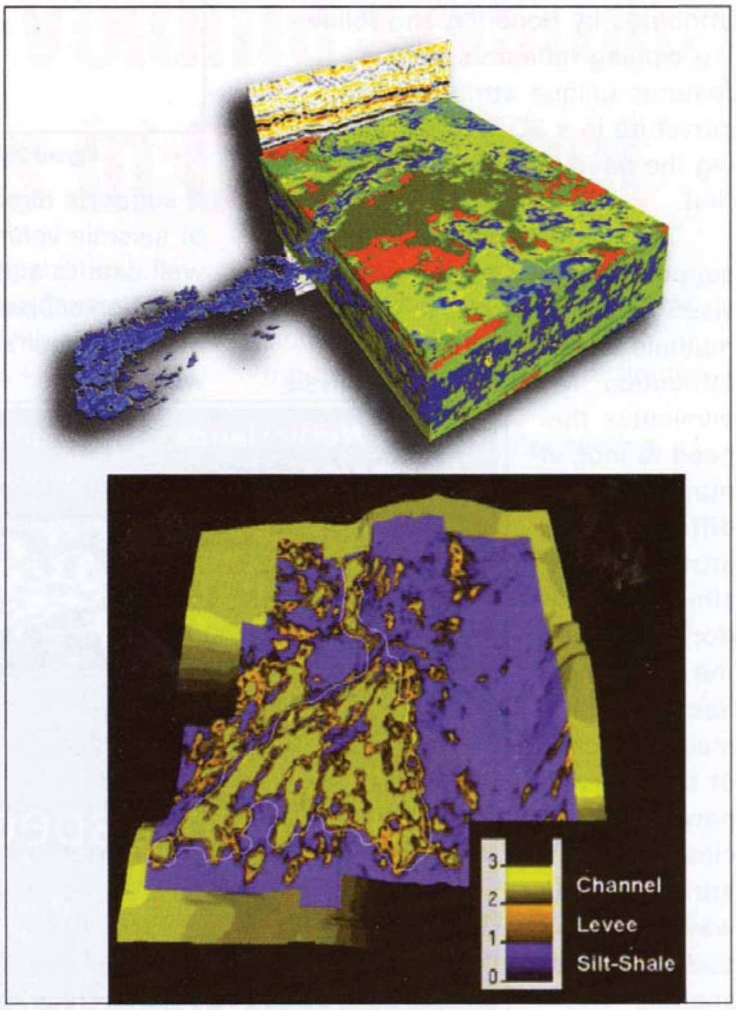

Figure 4: Seismic facies analysis. Top: unsupervised mode. The resulting bodies have similar attribute responses. Interpretation is done afterwards. Bottom: supervised mode. The patterns have similar attribute responses as the learning set that was created from attributes extracted at manually picked example locations. Shades indicate the confidence in the results.

Figure 3 shows an example of chimney cube usage for fault seal analysis. Time-slices through a fault cube (created by a similar process but now the network has learned to recognize faults) are overlain by time-slices through a chimney cube. Leaking faults are visible in both cubes. The appearance in the chimney cube is characterized by a pock-mark behavior along the fault strike line.

Seismic Facies

Neural network meta-attributes can also be used for seismic facies analysis. OpendTect supports two types of neural networks: supervised and unsupervised. The unsupervised method is a form of clustering. The resulting 2D grids and 3D body cubes reveal areas in the dataset with similar attribute responses. What these areas mean in terms of lithological and petrophysical variations remains to be interpreted. In supervised work the network is trained on known or interpreted examples. The patterns in the 2D grids or bodies in 3D space thus have a meaning: they represent areas with similar responses as observed in the learning set. Fig. 4 shows examples of both approaches.

Rock property prediction

In the previous examples networks were used to cluster data (unsupervised) approach or networks were trained on examples that were picked by the user (supervised approach). When well logs are available the supervised approach can also be used to create the learning set for the neural network. The input comes from seismic attributes such as acoustic and elastic impedance and AVO attributes that are extracted in a sliding window along the well tracks. The desired output is the corresponding well log property. When the seismic data is in two-way time the logs are converted from depth to time and re-sampled to the seismic sampling rate. Typical target logs are porosity, Vshale, Sw and lithology. Figure 5 shows an example where this method was used to convert an acoustic impedance volume to a porosity volume. In this case there were 4 wells. Porosity logs showed a decreasing trend with depth. The input to the neural network consisted of a small window of acoustic impedance values and the reference time to capture the depth trend. Fig. 5 shows the neural network performance at the end of the training and the result on one random line.

Conclusions

Multi-volume seismic attribute analysis plays an increasingly important role in seismic interpretation work. Primarily attributes are used for visualization and integration purposes. In this paper we showed various examples of combining these primary attributes into a new "meta attribute" with neural network technology. All examples were generated in OpendTect with dip-steering and neural network plugins.

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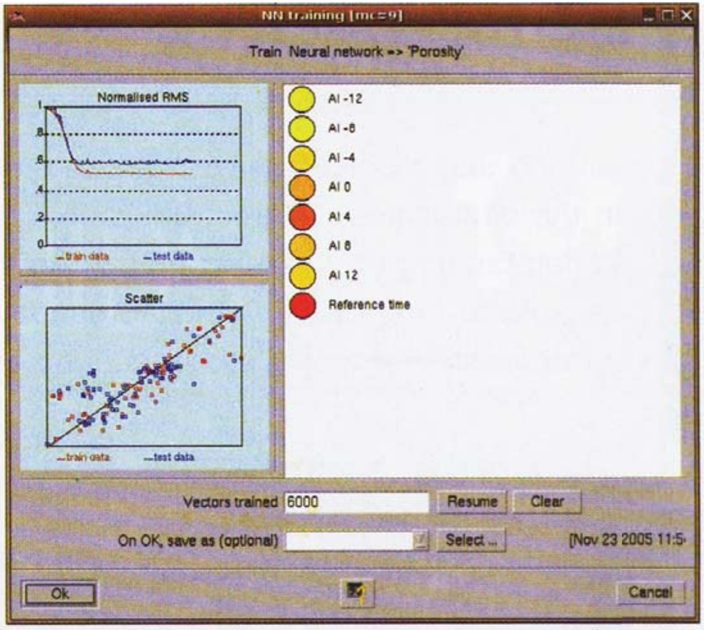

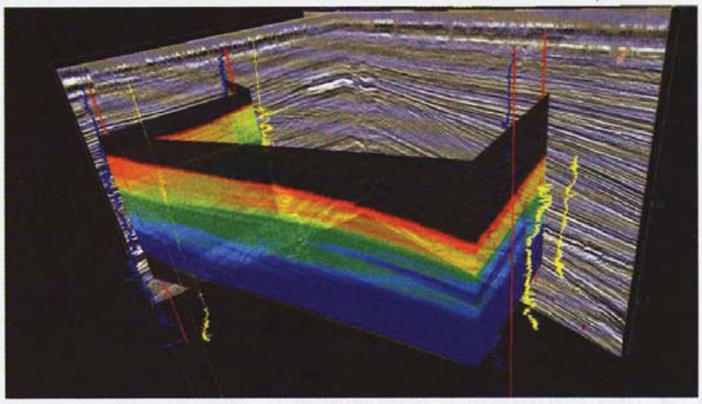

Figure 5: Porosity prediction from Acoustic Impedance. The learning set is constructed from examples extraxted along the well tracks. Top: neural network training performance. Neural network inputs are shown on the right. Note that reference time is included to capture the decreasing porosity vs. depth trend. Bottom: random line from the porosity volume through the wells. Porosity logs are shown in yellow.

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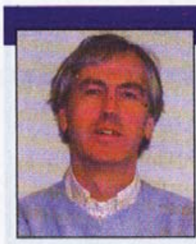
ABOUT THE AUTHOR



Paul de Groot is managing director of dGB. He worked ten years for Shell where he served in various technical and management positions. Paul subsequently worked four years as a senior research geophysicist for TNO Institute of Applied Geosciences before co-founding dGB in 1995. He has authored many papers covering a wide range of geophysical topics and co-authored a patent on seismic object detection. Paul holds MSc and PhD degrees in geophysics from Delft University of Technology.