3-37 # VOLUME TRANSFORMATION BY WAY OF NEURAL NETWORK MAPPING

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Summary

In this paper we present a method for transforming one, or more seismic input cubes into one, or more 'seismic' output cubes by way of neural network mapping. Both supervised and unsupervised learning approaches can be used to transform the data into:

1. Segmentation volumes: revealing 3D bodies with similar seismic response (unsupervised approach).
2. Class volumes: revealing 3D bodies with a specific geological or petrophysical meaning (supervised approach).
3. Prediction volumes: quantified petrophysical information (supervised approach).

Networks are trained on representative sets of data points. Input can be any relevant information (amplitude, derived attribute, spatial information) that can be supplied at every spatial location. Information can be extracted from multiple volumes such as reflectivity, near-offset stack, far-offset stack, gradient, intercept, acoustic impedance or 4D-difference stack. The method therefore has general applicability and is well suited for AVO and 4D work.

Examples of segmentation, classification and prediction volume transformations will be given.

Methodology

The first step in both supervised and unsupervised learning approaches is to create a representative set of data points for training the neural network. Careful selection of seismic (waveforms, single-trace, multi-trace) attributes is an important step in the procedure, especially in the case of unsupervised networks.

In the unsupervised mode data points are selected at random positions in the cube. Attributes are extracted at these points and given to an Unsupervised Vector Quantiser (UVQ) network. The network learns to cluster the input into a pre-defined number of segments. Application of the network to the entire volume(s) yields two outputs at every sample position: the segmentation result i.e. the index of the winning segment and the match i.e. a measure of confidence in the segmentation.

In supervised volume transformation the training (and test) data sets are constructed from seismic traces and corresponding log traces (Fig. 1). A log trace is a re-sampled version of a well log. When the seismic data is in two-way time, the log trace is converted to time using the sonic log. In prediction experiments the resulting trace is subsequently resampled to the seismic sampling rate using an anti-alias filter. In classification experiments the target log (e.g. litho-class) has only integer readings and thus cannot be resampled using an anti-alias filter. In these cases the log trace is resampled by outputting the most frequent integer value in a window around the sample position.

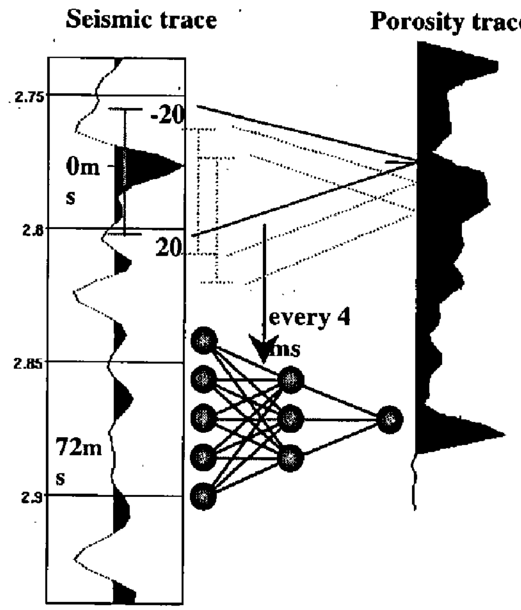

Fig. 1 Example of a porosity prediction by way of neural network mapping. The training set is constructed from information extracted along the well track. Input seismic trace(s) and target well log trace (depth-to-time converted and resampled version of the well log) need to be completely aligned for optimal results. Wells can be real or simulated. To avoid stretch / squeeze and miss-pick errors we generally prefer to use the synthetic seismic trace instead of the measured seismic trace when using real wells. The real seismic traces are then rescaled to the synthetic amplitudes when applying the trained network yielding the desired 3D porosity prediction volume.

Log traces can be derived from real and/or simulated wells. Seismic traces can be real as well as synthetic. Ideally we want to train a network on real seismic trace information and real well data. This requires that the seismic trace and the corresponding target log trace be completely aligned over the entire target. In practice we are dealing with miss-picks and log trace depth-time conversion problems resulting in unaligned data that cannot be used to construct the required training and test sets.

It is common practice to solve such problems by stretching and squeezing the synthetic seismogram in order to force a fit with the real seismic trace. Using such a 'corrected' sonic log would be one possible way to ensure that the seismic trace and the log trace are aligned. In that case, the miss-pick must also be updated manually. Although feasible, this is an enormous task, which lacks theoretical support and is considered more 'fudge' than a real solution.

A better way that automatically ensures full alignment between seismic information and log information is by using the synthetic seismic trace instead of the real seismic trace. The reason is that the synthetic seismic trace and the well log trace are created in exactly the same way, hence they have the same stretch / squeeze / miss-pick errors and thus the alignment is perfect. The trained network represents the optimal mapping from seismic response to target log response. Before applying this trained network to the real seismic data, we must ensure that synthetic and real seismic data are scaled in the same way. This can be achieved by applying a linear transformation from one to the other, or vice versa.

Comparison of the predicted log response from synthetic seismic and from real seismic with the actual target log response at the well locations reveals the quality of the transformation and seismic response at well locations.

Examples

Examples of segmentation, classification and prediction volume transformations will be given.

The first example shown in this abstract is a segmentation approach (Fig. 2). The seismic reflectivity data is segmented into 10 segments based on energy, trace-to-trace similarity and frequency. Energy and trace-to-trace similarity are computed in two different time gates, hence yielding a UVQ network with 5 inputs. Segments correspond to stratigraphic sequences, which can be easily separated using 3D-visualisation software.

The second example deals with a porosity prediction (Fig. 3). The training set was constructed from simulated wells. The real wells are used as blind test locations. A fully connected Multi-Layer-Perceptron neural network was trained to predict porosity from 40 ms. of synthetic waveforms and Acoustic Impedance.

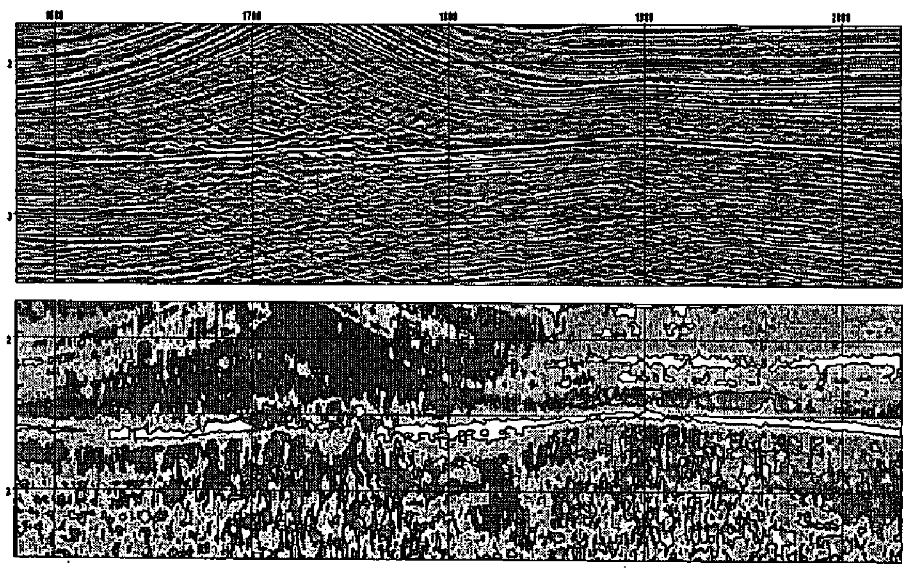

Fig. 2 Segmentation example. The seismic data is segmented by a UVQ network in 10 segments based on 5 attributes: 2 energy, 2 trace-to-trace similarity and frequency.

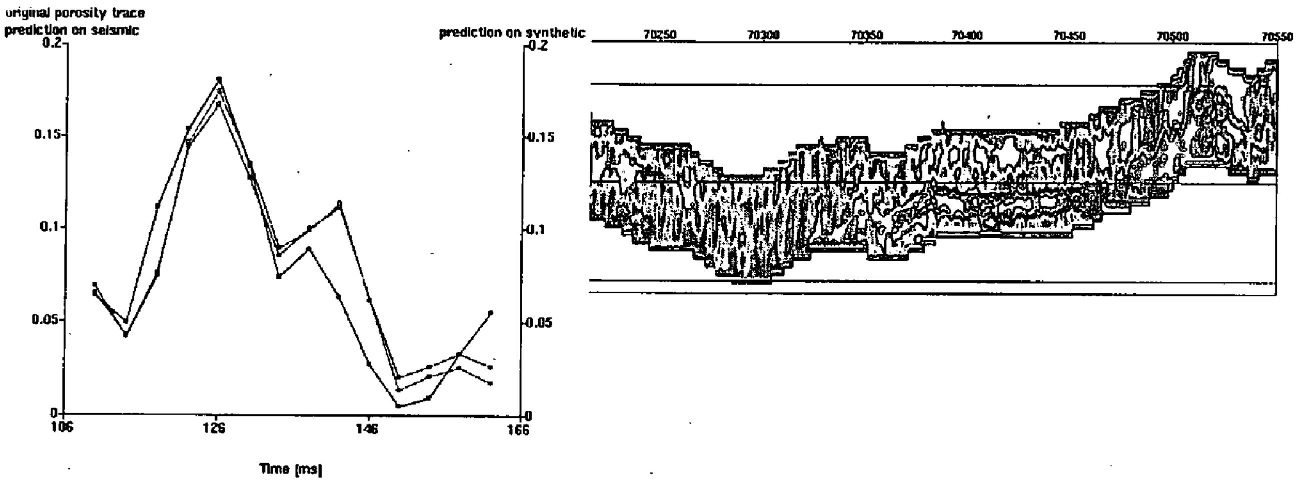

Fig. 3 Prediction example. Seismic waveforms and acoustic impedance are mapped to porosity by a fully connected Multi-Layer-Perceptron neural network. An arbitrary inline from the prediction cube is shown on the right. On the left the original porosity trace at one blind test well location is compared with the predicted trace from synthetic and real seismic data.

References

de Groot, P.F.M., 1999. Seismic Reservoir Characterisation Using Artificial Neural Networks. 19th Mintrop-Seminar, 16 – 18 May 1999, Münster, Germany.