F-26 SELECTING AND COMBINING ATTRIBUTES TO ENHANCE DETECTION OF SEISMIC OBJECTS

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Abstract

This paper describes recent experiences with the seismic object detection method developed by Meldahl et al. (1998 and 1999). In this patent pending method supervised or unsupervised neural networks are used to transform multiple 'directive' attributes into 'object probability' classes. The method is used a/o to detect seismic chimneys and faults (Heggland et al., 1999 and 2000). Selection of attributes is a crucial step in the procedure, especially in the unsupervised mode. In this paper we discuss methods and criteria to optimize the attribute selection process. Furthermore, we compare single-attribute interpretation versus the multi-attribute neural network approach and we conclude that the latter method is superior for seismic object detection purposes.

Introduction

Seismic objects are spatial elements with an observable size and orientation with a seismic response that differs from the surrounding response. Objects can be solid in which case the internal texture differs, or they are two-dimensional features characterized by a break in the response. Many workers use attributes to better visualize and interpret objects. Often the interpreter extracts multiple attributes, which immediately causes two interpretation problems:

1) the object is not uniquely defined by any of the extracted attributes and

2) attributes do not discriminate between objects of different geological origin.

The method promoted by Meldahl et.al. solves both problems by re-combining extracted attributes using neural network technology. Two learning approaches are used: supervised and unsupervised. In unsupervised mode the network segments (clusters) given attributes into a user-defined number of segments. The network is trained on a representative sub-set of data points, typically attributes extracted at a regularly sampled 3D grid. Application of the trained network yields a clustered seismic response cube. It remains the interpreter's task to determine what these clusters mean in terms of geological or petro-physical variations. The choice of input attributes determines the result, as different attribute assemblies yield different output clusters. Also in supervised mode the attribute assembly is important but here it merely affects the quality of the result and not the meaning. In supervised mode a neural network is trained on data points selected by the user to classify the response into two classes: object or non-object. Application of the trained network yields an 'object probability' cube.

Figure 1 shows one line from a neural network generated probability cube. In this case the network recombined nineteen attributes to predict the probability of the seismic position to belong to a seismic chimney. One of the attributes contributing to this result is a trace-to-trace similarity calculation. The single attribute result is shown in the same Figure for comparison. It shows that the neural network improved the chimney definition and was able to distinguish between chimneys and other objects with low similarity such as faults and low coherent reflective sequences.

Attribute selection

Attribute selection is based on experience, common sense, the directivity principle and statistical support tools. Years of experimentation at dGB and Statoil led to a whole range of new attributes and attribute assemblies that are known to be effective for detection of chimneys, faults and other objects of interest. Much work was done in a trial and error mode guided by common sense. Most new attributes and attribute assemblies follow the directive principle, which states that information is optimal along the direction of the object of interest. Processing, filtering and attribute extraction should therefore ideally be done along the user-defined, or data-driven direction. For example seismic chimneys are vertical disturbances of the seismic response. To decide whether or not a position belongs to a chimney we should also look above and below the current position. In other words attributes extracted in vertically aligned windows ought to be similar if the position is a chimney. This concept allows the network of Fig. 1 to distinguish between vertical disturbances and other local disturbances. The directivity principle is not only utilized in the alignment of attribute extraction windows. Also the extraction window itself can follow the object of interest. For example the similarity attribute, which calculates the normalized Euclidean distance between two or more trace segments is much better defined if the trace segments belong to the same seismic event. This requires knowledge of the local dip and azimuth, which can be calculated a/o with a sliding 3D kf-transform (Tingdahl, 1999). Dip information opens a whole category of powerful directive attributes that are calculated in data-driven shapes such as 'warped' disks, cubes or cylinders.

Taking into account that most attributes can be calculated with different parameter settings it is thus possible to calculate an almost infinite number of attributes. Most attributes will be highly correlated and therefore increasing the number of attributes generally does not increase the quality of the results. In practice we have enough training examples to worry about random correlation between attributes and objects of interest. So increasing the number of attributes will neither deteriorate the quality of the results. However, processing time will increase and may reach unacceptable limits. Therefore, in supervised mode it is good practice to compute a co-variance matrix between all selected attributes of the training set and the target variables (object or non-object, represented by the values one and zero). The final attribute assembly is based on this output and taking into consideration processing time constraints.

Conclusions

Seismic objects can be more clearly defined if the detection is based on multiple attributes that were combined by a neural network to 'probability classes'. In this process the choice of input attributes and the use of directivity is of crucial importance. A co-variance matrix between selected attributes and target variables of the training set may help to define the attribute assembly in the case of supervised learning.

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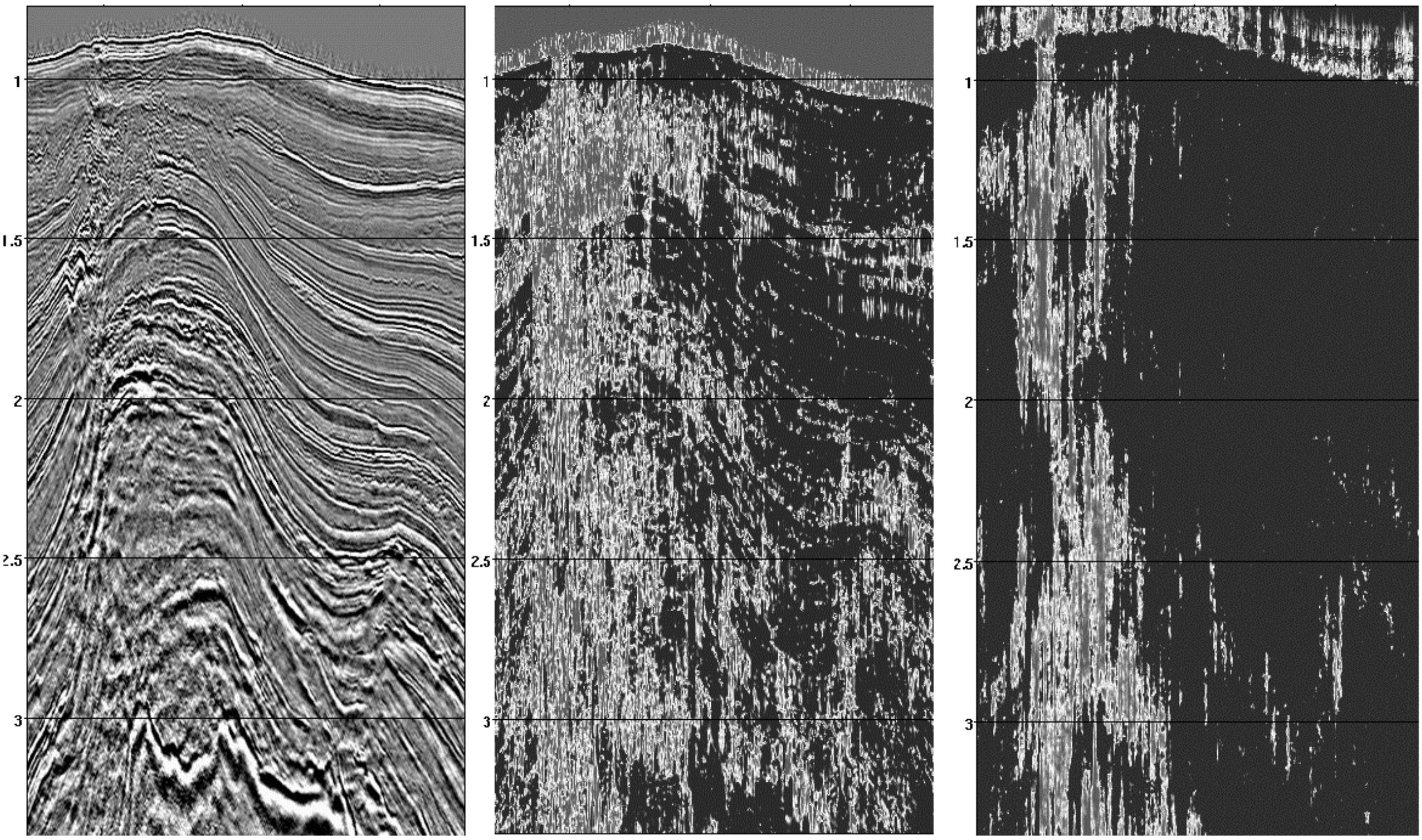

Figure 1. Comparison of standard seismic (left), single-attribute 'similarity'section (middle) and neural network detected chimneys (right).