Assessing hydrocarbon risk with neural network classification methods

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Abstract

Risk assessment for hydrocarbon-saturated reservoirs can be improved using neural network classification methods when combined with interpreter's knowledge. Training data selected over background events and known hydrocarbon deposits permits calibration of untested reservoirs, which in turn improves the pre-drill prediction process as well as the range of possible outcomes, thus providing a measure of the uncertainty. The Gulf of Mexico examples presented here demonstrate the potential for improved reservoir assessment and exploration risk reduction with the aforementioned technique.

Introduction

With the proliferation of 3D seismic data, and the reduced computational costs of prestack data processing, exploration and exploitation methods in mature basins such as the Gulf of Mexico are essentially now a function of economic bencRPIrks and known reservoir analogy comparisons.

Given sufficient high fidelity seismic coverage over reservoirs of equivalent geology and contemporary environment, seismic characteristics are compared and reservoir description inferred. For low acoustic impedance hydrocarbon-saturated sands encased in shales, amplitude strength and phase characteristics often are diagnostic. In addition to these two "basic" seismic attributes, inexpensive computing costs have resulted in prestack attributes that are now used in conjunction with the standard direct hydrocarbon indicators.

With the availability of multiple seismic attributes, the ability to use a multi-attribute approach such as multi-attribute multi-linear regression or neural network techniques is advocated. In recent years, various publications and presentations have shown that conditioned neural networks can improve seismic reservoir description. Hampson, et. al, (2001) demonstrates the conditioning of seismic data to predict log properties. Ross (2002) improved AVO resolution using Vp/Vs well log data to condition seismic AVO attributes with neural networks. In these two publications, abundant well data was available. This is not always the case, especially in mature basins with wells prior to modern logging tools. In these instances training of seismic data comes from geoscience teams and their experience in the area.

A multi-attribute approach has been demonstrated for chimney detection by Aminzadeh, et al. (2002) and by others, and is extended in this article for reservoir prediction with AVO attributes.

Description of neural network technique

We follow the “meta-attribute” concept of Aminzadeh et al. (2002) and Aminzadeh and de Groot (2004). Essentially, it is preferential selection of set of attributes that when combined through a neural network with proper training, using interpreter’s insight. The result is a single, direct and optimized meta attribute for a specific geologic object, for reservoir property (e.g. salt, gas chimneys, reservoir quality sands, fluid factor, etc…)

A generalized workflow of the approach is highlighted in Figure 1. This method is similar to the conventional neural network-based method with the important addition of the "Interpreter's Knowledge" box. The main advantage of this approach is the versatility in the training process. For example, let us assume the focus of the interpretation work is to highlight areas with higher probability of hydrocarbon accumulation. We wiil refer to this as Reservoir Probability Index or RPI.. Step one is to examine the data set and identify areas to be known or likely areas with hydrocarbon (from well data or interpreter's insight). Such points are identified by an (x) in Figure 1. We also identify representative areas, which are unlikely to have hydrocarbon. Those points are shown by a (o).

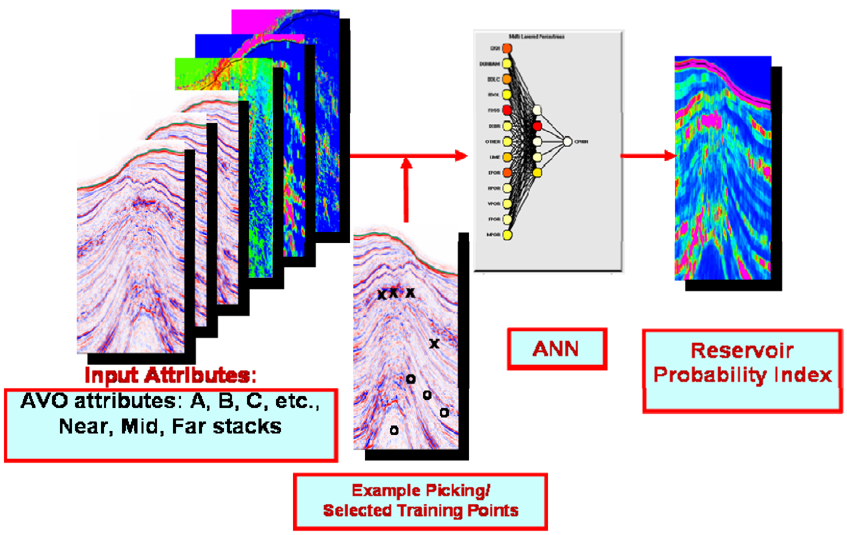


Figure 1: Generalized work flow

In step two, which encompasses attribute calculations, training, testing, and an implicit non-linear transformation of all the pre-stack attributes is created termed the "Hydrocarbon Meta-Attribute". In an ideal situation, the Hydrocarbon meta-attribute should highlight only those areas within the 3-D volume that correspond to hydrocarbon-bearing reservoirs and nothing else. Practically, we are creating a " Reservoir Probability Index" or RPI volume with large probability values associated with those areas that have closer to overall "likeness" to the non-linear combination of attributes represented by the "known" or interpreted hydrocarbon bearing reservoirs. It has to be emphasized that since several partial stack volumes of data are input to the neural network, the entire set of pre-tack attributes, including those related to AVO are implicitly used in the training. Thus, this approach can be considered as a generalized AVO inversion approach.

Data Examples

Based on a meta attribute approach that combines interpreter's knowledge and capabilities of a neural network as described above, two tests are presented here. The first one uses the full and partial stacked data volumes (test A). The second one uses the full stack and various AVO attributes (test B). Figure 2 shows a horizon slice through the full stack seismic volume over a known producing reservoir. The gas/oil reservoir varies in gross thickness from 3 to 25 m, and has been penetrated by approximately 10 wells. The amplitude strength of the reservoir is sufficiently stronger than the surrounding background media, which classifies the seismic response as a bright spot. Displayed on top of the slice are training points within and outside of the bright spot. These are the training points used as input into the neural network. As described above, attributes and computations from these attributes are sampled at the classified points and used for training a neural network. For each test, an RPI was computed and redisplayed as a horizon slice to establish control and validation. Figure 3a shows the result using the partial stacks (Test A), and Figure 3b shows the results using various AVO attributes (Test B).

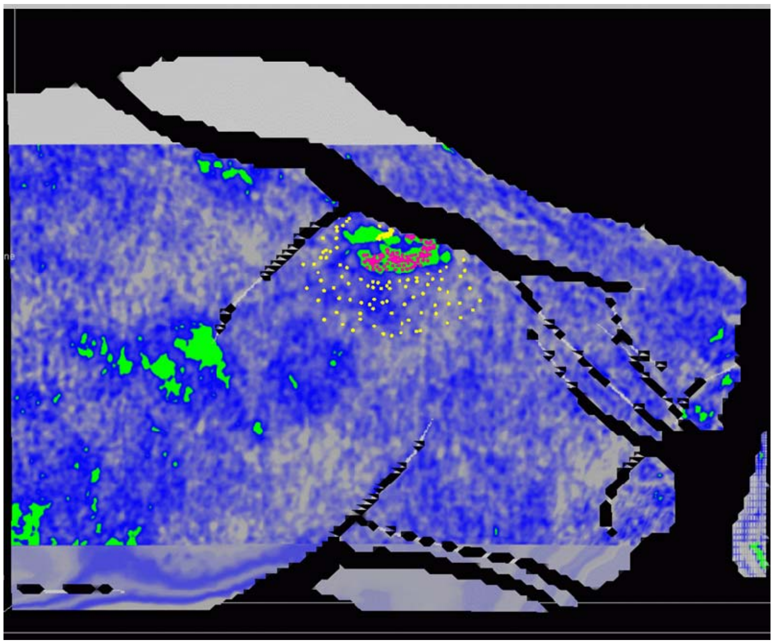
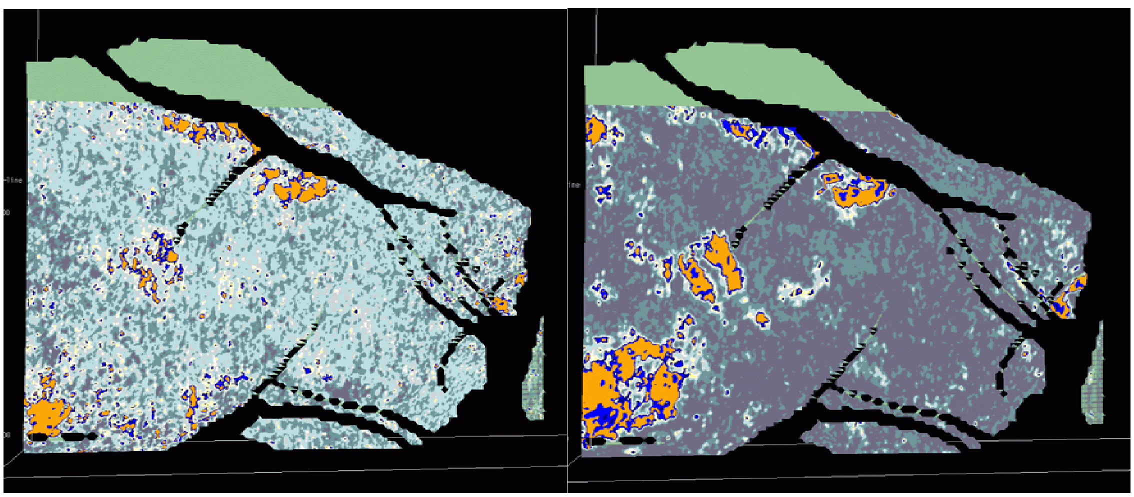


Figure 2: Full stack horizon slice showing the DHI extent (green) and selected training Data



a *b*

Figure 3: a,Validation of Test A, b,Validation of Test B, higher RPI denoted by orange color

Results from both Tests A and B indicate the training sets selected were adequate, and the validation of the RPIs is acceptable. While both RPIs are similar to each other as well as the inferred hydrocarbon extent of the DHI, there are some differences. In particular uniformity of the Test B RPI over the known hydrocarbons (just below the major fault and to the far right), and the diminished down-dip, inter-slope anomalies that are hard to explain geologically are better portrayed than in the RPI slice from Test A. While there are no penetrations in the down dip amplitude anomalies, the RPI using AVO attributes presents this anomaly as a less likely commercial reservoir. Both RPIs are similar in that definition of the trained pay/non-pay interface, and the separate hydrocarbon compartment to the left of the training points. With the testing and validation phase satisfied, the meta-attribute transform for Test B was then applied to a second producing reservoir horizon using only the training points from first reservoir. The second reservoir is penetrated by a number of wells and is 3 to 20 m thick with oil and gas accumulations. The results from this neural network application are shown in Figure 4, and indicate a strong similarity to the training reservoir, which is from well log data quite similar.

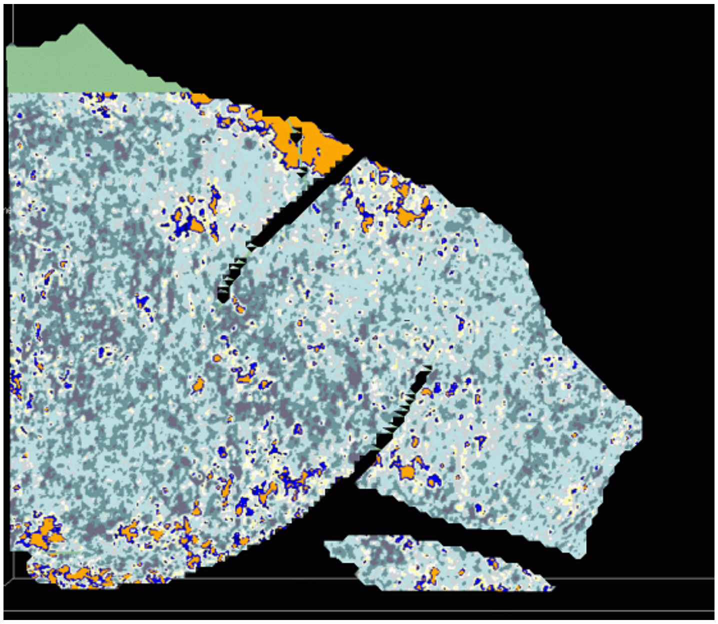


Figure 4: RPI display of deeper reservoir. This neural network was constructed using the training points from the other reservoir

Conclusions

A neural network classification approach has been demonstrated using two different attribute sets with two different reservoir levels (with similar reservoir characteristics). While the use of AVO attributes for one test appears to have yielded higher fidelity results than the partial stack attributes, both tests indicate the usefulness of the multi-attribute approach for predicting hydrocarbon and or reservoir similarity (i.e. how attributes from one reservoir can predict the reservoir characteristics of a second).

Please note that the contrast between the two different sets of attributes is expected to vary as a function of S/N, and in some data sets where the S/N is low, the partial stack might result in better training and validation results.

The results from this case study illustrate an alternative way to assess seismic reservoir characterization using multiple attributes and high quality 3D seismic data.

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Acknowledgments

The authors thank Newfield Exploration Company and partners for permission to present this work, as well as WesternGeco for permission to present their seismic data. Special thanks to Steve Robertson for his interpretation guidance with this project, and Julia Naumenko for her input with data training and conditioning with the neural networks.