Neural Network Applications of Seismic Attributes for Predicting Porosity and Production

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The introduction of seismic attributes to the exploration world has brought another dimension to the seismic data interpretation. Further development has introduced another approach known as multi-attribute analysis which uses artificial neural networks (ANNs) to combine the multiple attributes to predict desired reservoir properties. Seismic attribute analysis using neural network applications has become an important tool for understanding the physical features and internal structure of reservoirs. Understanding such features is vital to provide effective strategies for exploration and exploitation in both new and old survey areas.

The primary objective of this study is neural network applications of multi-attribute analysis to reveal reservoir features. Figure 1 shows a schematic display for attribute analysis using ANNs. Neural networks are composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems (Christos and Dimitrios, 1996). A strong motivation for using ANNs is to deal with the non-linear relationship between seismic derived information and well log data. In this study, two neural network approaches were used for attribute analysis. First, supervised neural network analysis was applied to instantaneous attributes derived from pre-stack migrated seismic data to predict porosity and production for Member A and to predict porosity distribution for Member B. Second, unsupervised network training was applied to the predicted porosity and production values to identify potential zones for further hydrocarbon exploration. Figure 2 shows a diagram for a multilayer neural network structure as an example for supervised training approach.

In order to predict the porosity distribution for the members A and B, a backpropagation algorithm was applied using five instantaneous attributes for inputs and porosity values for targets. The procedure of creating the input training set for the supervised ANN (in this case backpropagation) analysis starts with exporting sub-volumes for each of the five attributes. The next step was to average these attribute values within a 200 feet radius around the wells. Attribute values from nine CMP locations were averaged around each well and assigned to the input matrix. For supervised porosity prediction, seventeen wells were available for the Member A and eight wells for the Member B. Figure 3 is an illustration of the structure of the input matrix derived from the attribute values of the Member A. In order to improve training performance, the initial input training set was replicated five times for the Member A (ten times for the Member B). Furthermore, five percent Gaussian noise was added to the replicated data (Figure 3). I also investigated another approach designed to reduce the dimensionality (number of rows) of the input training matrix. This approach was to perform a polynomial fit to the attribute values. A six degree polynomial fit was applied to the attribute values calculated at each well location to obtain 7 polynomial coefficients representing the attributes exported from sub-volumes (Figure 3).

The following process was used to obtain targets which consisted of computed and actual porosity values. Porosities corresponding to the thickness of the sub-volumes were averaged to obtain one average value for each well. These averaged porosity values were assigned to the target matrix at the corresponding well positions (Figure 3). These target values (averaged porosity values), were only replicated; namely, noise was not added to the targets.

The iterative training performance and the relationship between network outputs and targets were monitored using both performance and regression plots. After training is completed (reaching mse level, maximum number of iterations or validation stop), the trained network parameters (weights and biases) were applied to the entire data set (attributes at non-well locations) to predict porosities for the entire survey area. The same processing steps were done for production prediction in the Member A and porosity prediction in the Member B. The next step is to identify zone(s) with high porosity and production values using self-organizing feature map (SOFM) also called as Kohonen map which is the most known unsupervised neural network algorithm. The SOFM results with and without polynomial fit show that predicted porosity and production values classified into five groups help distinguish facies with high porosity and production values that might be a potential for further exploration in the field.

Supervised ANN training results showed that predicted porosity values (especially high and medium porosity values) show a good correlation with production wells in the Member A. In addition, SOFM classification applied to predicted porosity and production values reveal a high porosity and production section which might be a possible target zone for further hydrocarbon exploration. The same supervised backpropagation training approach was also applied to the Member B to map the porosity distribution. However, due to the limited number of production wells available for the Member B, production prediction was not applied. Even though production prediction was not applied to the Member B, it is worth to note that the two production
wells available for that level are found to penetrate a high porosity section on the porosity prediction map.

**Figure 1**

Schematic display for multi-attribute analysis. Calculated attributes are combined through the use of neural network algorithms (modified from Barnes 2001).

**Figure 2**

Example diagram for a multilayer neural network structure. Here \( p(i) \) are the inputs, \( S \) is the neuron number, \( [W] \) is the weight matrix, \( [b] \) is the bias matrix, \( T_f \) is the transfer function, and \( a_i \) is the output from each layer (modified from Hagan et al., 1996).

**Figure 3**

Diagram showing the dimensionality of the training input data set before and after polynomial fit. Noise addition or polynomial fit is not applied to the targets.