Seismic Signal Interpretation and its Application in the Oil/Gas Exploration

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Abstract---The Seismic interpretation is one of the latest techniques to extract data and getting information on the geometry and physical properties of earth surface. The most important task in reservoir characterization is porosity interpretation which defines property of reservoir. This paper presents a work flow to determine porosity with the help of intelligent Caianiello neural network. Acoustic impedance-porosity relationship is given for the learning process of intelligent Caianiello neural network.

I. INTRODUCTION

Seismic interpretation is valuable tool for reservoir characterization prior to field development. It transforms seismic reflection data into quantitative rock property, which define reservoir. For seismic interpretation we are using intelligent Caianiello neural network.It is static and feedforward neural network. Static implies that the weights, once determined, remains fixed and do not evolve with time. Feed forward indicates that the output is not feedback.Thus; this type of network does not iterate to a final solution but directly translates the input signals to an output independent of previous input. The weighted sum of neural network's inputs is fed to a nonlinear transfer function which is known as the activation function to rescale the sum. A constant bias Θ is applied to shift the position of the activation function independent of the signal input. Neural networks with monotonically increasing activation functions are called multilayer perceptron (MLP).The two most important steps in applying neural networks to recognition problems are the selection and learning stages, since these directly influence the overall performance and thus the results obtained. Training of neural network is developed using the impedance-porosity relationships. Acoustic impedance is a function of both density and velocity. Density variations have some impact on acoustic impedance, but velocity variations are much more significant. Lab data indicate that at depth greater than 4000m, velocities are most sensitive to changes in porosity. Velocity changes resulting from changes resulting from changes in fluid type or pressure are small in comparison. [2].

II. SEISMIC DATA COLLECTION METHOD AND TOOL

Seismic data is a picture of the earth below the surface of the ground. Seismic data define different rock formations as layers of reflectors. Various rock types and fluids in the rocks, cause seismic reflection. Seismic data is collected in the field, processed in a computer than interpreted. The "Reflection Seismic Method" is a technique used to map 2D or 3D picture of the earth's subsurface. As shown in Figure 1, Sound waves are sending into the ground using energy source such as vibrators or dynamite. The sound wave passes through the earth and are reflected off, and transmitted through, the rock layers. A seismic crew goes into the field and collects the data.

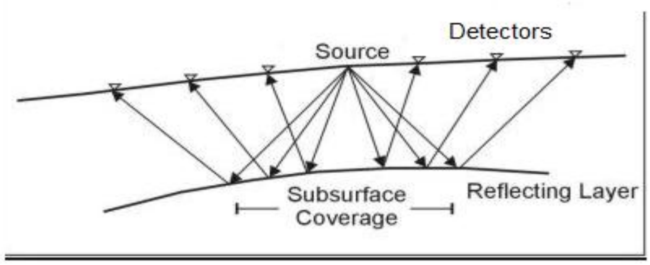

Fig. 1: Reflection Seismic Method

A geophone and receiver box is used in the field to receive seismic data which is known as seismogram. A seismogram is the record of ground movement detected by a seismometer.

III. POROSITY INTERPRETATION

Porosity is very important attribute to predict the presence and properties of the reservoir. In Figure 2, neural network is applied for porosity interpretation to improve the prediction of reservoir properties. Neural network is used to establish relationship between seismic response and porosity. Artificial neural network are used first through learning in an information environment known both for input and the desired outputs. Once trained, they can be applied to any new input dataset in a new information environment with known input but unknown output.

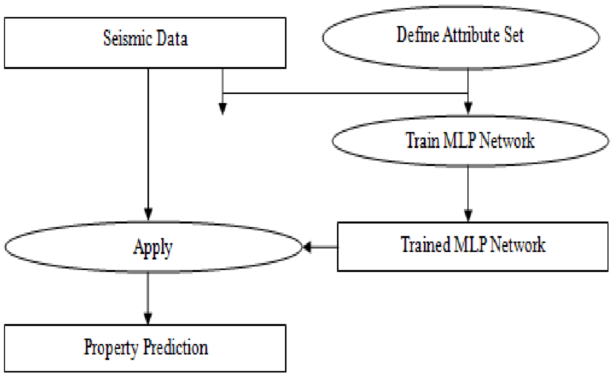

Fig. 2: Flow chart of Porosity Inversion [8]

IV. SEISMIC ATTRIBUTE SET

A block frequency-domain implementation with FFTs Combining Robinson seismic convolution model and Caianiello neural network, high-resolution nonlinear interpretation for seismic impedance has been completed.Training of neural network is developed using the impedance-porosity relationships by means of nonlinear petrophysical model.

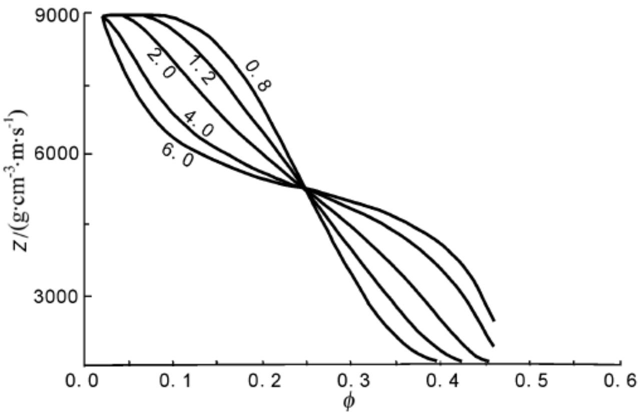

Fig. 3: Relationship between acoustic impedance and porosity corresponding to different nonlinear factors [1]

In petrophysical parameters interpretation, we use a nonlinear petrophysical model for the relationship between acoustic impedance and porosity as follows:

$$\frac{\emptyset_m(\emptyset_m-2\emptyset)}{\emptyset(\emptyset_m-\emptyset)} = \lambda\ln[\frac{z_p-z_f}{z_m-z_p}] \qquad (1)$$

where $\emptyset$ is porosity, $\emptyset_m$ is the maximum porosity of sandstones in the reservoir under study, z_p, z_f and z_m is P-wave impedance, the impedance of the pore fluid and the impedance of the rock matrix respectively. λ is a nonlinear factor that can nonlinearly adjust the functional form of the equation to an appropriate shape for practical data points. Figure 3 shows the performance of the model with different nonlinear factors and these fitted curves present S-style curve features. We see that for a fixed value of λ, different porosity ranges have distinct gradient that reflects different impedance porosity relationships. On the other hand, different λ values corresponding to different curves can give different models applied to different types of rocks.[1] A flexible expression can be obtained from Eq. (1):

$$\frac{\emptyset_m(t)(\emptyset_m(t)-2\emptyset(t))}{\emptyset(t)(\emptyset_m(t)-\emptyset(t))} = \lambda\ln[\frac{z_p(t)-z_f(t)}{z_m(t)-z_p(t)}] \qquad (2)$$

where $\emptyset(t)$ is the porosity curve in vertical time and $z_p(t)$ is the impedance curve. The accurate estimation of the time-varying nonlinear factor λ(t) for different lithology at different depth is a crucial point in petro physical parameters inversion. Fortunately, the Caianiello neural network provides an optimization algorithm to iteratively adjust λ(t) in adaptive response to lithological variations vertically along a well log.

V. Neuron Model For Seismic Interpretation

In Caianiello neural network each parameter becomes a time sequence instead of a constant value. Each neuron receives a number of time signals from other neurons and produces a single signal output that can fan out to other neurons.

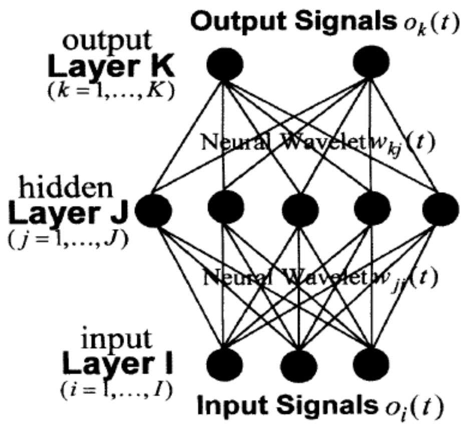

Fig. 4: Three Layer Three-layer Caianiello neural network architecture [6]

If the dataset used to train the neural network consists of an input matrix *Oi(t)* (i = 1,2 ..... I , where I is the number of input time signals) and the desired output matrix *Ok(t) (k* =1,2 ..... K, where K is the number of output time signals), one can select appropriate network architecture with I neurons in the input layer and K neurons in the output layer. For a general problem, one hidden layer between the input and output layers is enough.

The mapping ability of the Caianiello neural network results mainly from the nonlinear activation function in Eq. (1):

$$O_i(t) = f(\sum_{j=1}^{N}\int_0^t w_{ij}(t)O_j(t-\tau)d\tau - \theta_i(t) \qquad (3)$$

where the neuron's input, output, bias, and activation function are represented by $O_i(t)$, $O_j(t)$, $\Theta_j(t)$, and *f*, respectively, and *wj,(t)* is the time-varying connection weight. In general, the sigmoid nonlinearity of neurons is used.[6]Edge detection wavelet can be adjusted iteratively to match the network output signal and the desired output signal using Caianiello neural network algorithm. The cost function is the following mean-square error performance

$$E = \frac{1}{2}\sum_k\sum_t e_k{}^2(t) = \frac{1}{2}\sum_k\sum_t[d_k(t) - o_k(t)]^2 \qquad (4)$$

where dk(t) is the desired output signal, ok(t) is the network output signal. Edge detection wavelet for any neuron of all the layers can be updated recursively using error back propagation technology. Edge detection wavelet update formulation from the hidden layer to the input layer is:

$$\Delta w_{ji}(t) = \eta(t)\delta_j(t) \otimes O_i(t) \qquad (5)$$

Where $\otimes$ is the cross-correlation operation symbol, $\eta(t)$ is the learn rate. For the output layer, the back-prop error through the kth neuron is expressed as:

$$\delta_k(t) = e_k(t)f'[N_k(t) - \Theta_k(t)] \qquad (6)$$

where $f'(\cdot)$ is the derivative of nonlinear transform $f(\cdot)$,$N_k(t)$ is obtained by the following equation

$$N_k(t) = \sum_j w_{kj}(t) * o_j(t) \qquad (7)$$

For any hidden layer, $\delta_j(t)$ is obtained by the chain rule

$$\delta_j(t) = f'[N_j(t) - \Theta_j(t)]\sum_k \delta_k(t) \otimes w_{kj}(t) \qquad (8)$$

$N_j(t)$ is obtained by the following equation

$$N_j(t) = \sum_j w_{ji}(t) * o_i(t) \qquad (9)$$

A block frequency-domain implementation with FFTs for the forward propagation based on convolution operation and back propagation based on cross-correlation operation can be used in the Caianiello neural network.[1]

VI. CONCLUSION

In this paper we have discussed seismic interpretation which uses intelligent Caianiello neural network. Reflection seismic is very efficient method for the seismic data collection. Reservoir property is defined with the help of porosity prediction. Training of neural network is done using the impedance-porosity relationships by means of nonlinear petrophysical model.Seismic interpretation using neural network is fast & efficient. It can be used for oil & gas exploration to cope up with world's growing demand.

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