

Porosity prediction using attributes from 3C–3D seismic data

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ABSTRACT

The integration of 3C-3D seismic data with petrophysical measurements at wells can significantly improve the spatial description of porosity. Using multi-regression analysis and neural networks, a functional relationship between measured porosity logs and some seismic attributes can be derived at the well locations. Once derived, the relationship is applied to the seismic data and a porosity cube is generated.

We test this procedure on a 3C-3D seismic survey recorded over the Blackfoot oil field in Southern Alberta. A functional relationship between porosity and P-P and converted to P-P time P-S seismic attributes is determined at thirteen well locations. A cross-validation test is used to determine the meaningful attributes. A porosity cubes are generated and high porosity anomalies are interpreted as sand channel.

INTRODUCTION

Well observations provide good vertical resolution of geologic strata, but are at sparse locations. In contrast, 3C-3D seismic method provides dense and regular areal sampling but with considerably lower vertical resolution. The integration of 3C-3D seismic data with petrophysical measurements at wells can significantly improve the spatial description of porosity. However, the relationship between the porosity and some seismic attributes might not be obvious and furthermore, difficult to derive from the theory. To overcome the problem, we choose to derive statistical, rather than theoretical relationship. The approach is called a data-driven (Schultz et al., 1994) or statistical methodology.

METHODS

In general, the relationship (in time domain) between the porosity log and the seismic attributes can be written in the following form:

$$P(x, y, t) = F[A_1(x, y, t), A_2(x, y, t), \dots, A_M(x, y, t)] \quad (1)$$

where:

$P(x, y, t)$ – porosity log as a function of coordinates x, y, t

$F[\dots]$ – the functional relationship

A_i – seismic attributes, $i = 1, \dots, M$

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The functional relationship can be found using linear multi-regression analysis. The first step is to convert the porosity logs from depth to time with the sampling rate of the seismic data. Then we construct the following equations:

$$P_t = W_1 A_{1t} + W_2 A_{2t} + \dots + W_M A_{Mt} + C \tag{2}$$

where:

$t = 1, \dots, N$ – denotes time samples

$W_i, i = 1, \dots, M$ – weights to be determined

C - constant

The weights are found by least-squares optimization.

A more advanced approach is to use convolution operators instead of constant weights in the regression analysis:

$$P_t = W_1 * A_1 + W_2 * A_2 + \dots + W_M * A_M + C \tag{3}$$

where * denotes convolution.

In the case of an L-points convolution operator, there are $L \cdot M$ unknown weights to be determined by the least-squares optimization.

The discussed method would perform well if the functional relationship between the porosity log and the seismic attributes is linear. In the case of nonlinear relationship, we may apply non-linear transform to the seismic attributes prior to the least-squares optimization or use neural networks as a prediction tool. Figure 1 shows schematically the basic architecture of a multilayer feedforward neural network.

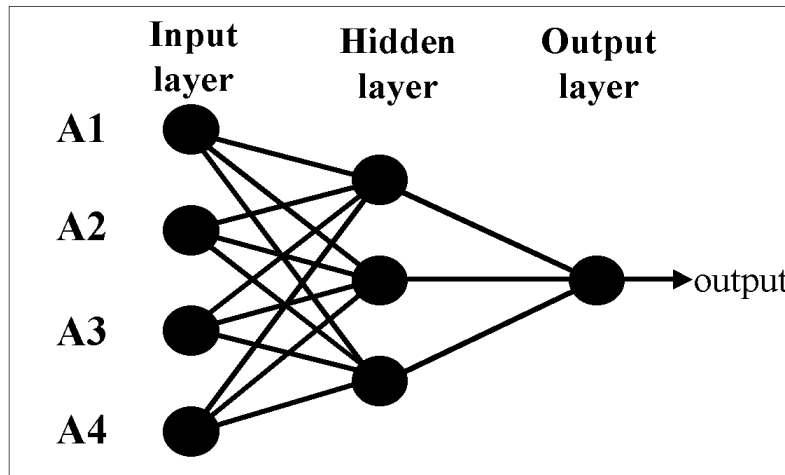


Figure 1. Basic neural network architecture. In this example, there are four input attributes, three neurons in the hidden layer and one log sample as an output.

The neural network consists of a set of neurons that are arranged into two or more layers. The neurons are connected in the following fashion: inputs to neurons in each layer come from outputs of previous layer, and outputs from these neurons are passed to neurons in the next layer. Each connection represents a weight. The neural network is completely defined by the number of layers, neurons in each layer, and the connection weights. The process of weights estimation is called training. Most of the training methods are based on the gradient back propagation technique (Masters, 1993). A training set is required and the weights are modified iteratively, so that the outputs of the network match closely the target outputs.

MODEL-BASED CONVERSION OF P-S DATA TO P-P TIME

To simultaneously use the seismic attributes extracted from P-P and P-S data, we have to convert the P-S data to P-P time. To do so we need P-S velocity information. The two-way zero-offset P-S travel time t_{ps} to a particular depth z is:

$$t_{ps} = \frac{z}{V_p} + \frac{z}{V_s} = z \left(\frac{V_p V_s}{V_p + V_s} \right) = \frac{2z}{V_{ps}} \quad (4)$$

where $V_{ps} = 2 \left(\frac{V_p + V_s}{V_p V_s} \right)$ is defined as a P-S pseudo-velocity, and V_p and V_s are the P-wave and S-wave velocities.

The model-based conversion scheme is done in the following way:

- at the well locations compute the P-S pseudo-velocity logs and V_{ps}/V_p logs:
- using the computed P-S velocity logs convert the V_{ps}/V_p logs into P-S time
- build a 3-D V_{ps}/V_p model in P-S time by 3-D interpolation
- compute the P-P time for the each P-S sample using the following equation:

$$PP_{time}(n - th \text{ sample}) = \sum_{i=1}^n \left(\frac{V_{ps}}{V_p} \right)_i \Delta t \quad (5)$$

where:

Δt – sampling rate

Note that the sampling rate in the resulting seismic trace is not a constant due to varying V_{ps}/V_p ratio (Figure 2).

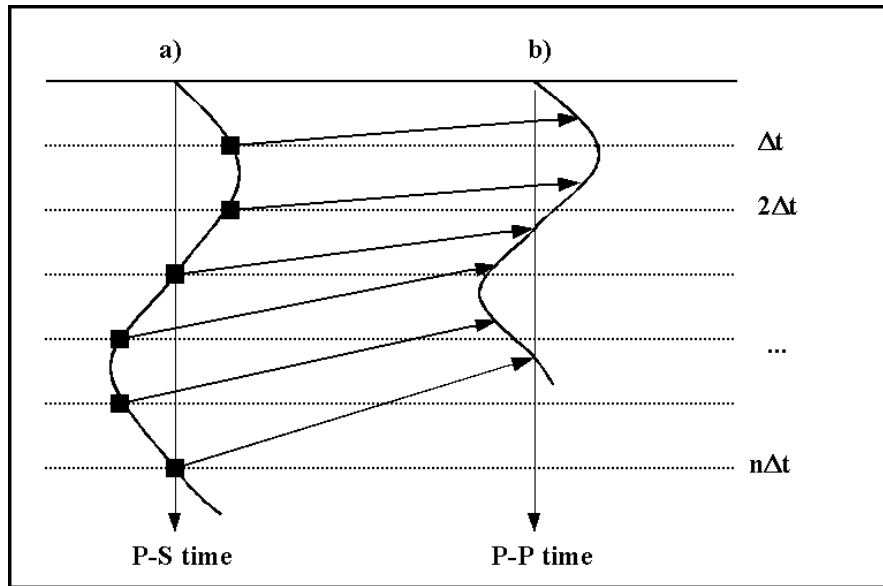


Figure 2. Conversion of P-S data to P-P time. Note the regularly sampled P-S seismic trace (a) (Δt – sampling rate) become irregularly sampled trace in P-P time (b).

The next step is to resample the converted to P-P time trace in a regularly sampled sequence with a constant sampling rate Δt . Let's compute the amplitude at the time location $n\Delta t$ (Figure 3a). We find the actual amplitude before and after this time, A_i and A_{i+1} , and then we compute the amplitude at time location $n\Delta t$ by linear interpolation (Figure 3b):

$$A_{n\Delta t} = A_i + \frac{(A_{i+1} - A_i)(n\Delta t - PP_i)}{PP_{i+1} - PP_i} \quad (6)$$

where PP_i is the computed P-P time for the i -th P-S sample.

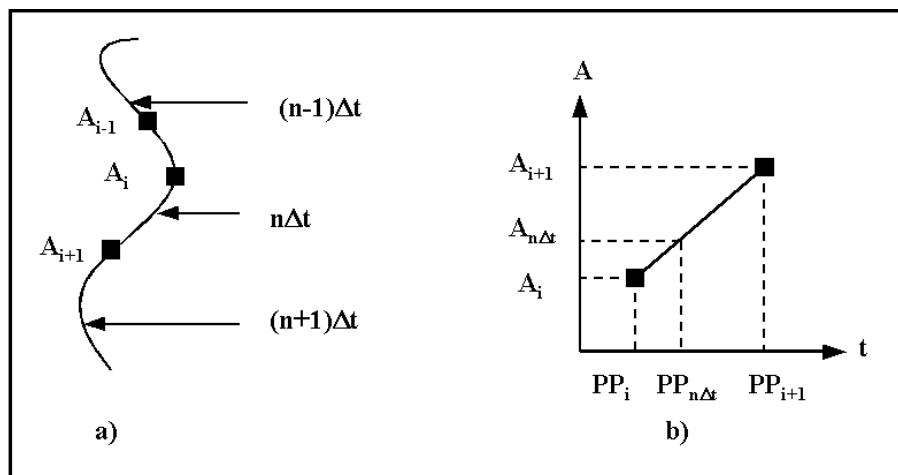


Figure 3: Resampling the converted P-S data to regularly sampled P-P time.

BLACKFOOT 3C-3D CASE STUDY

As an example of the techniques described in the previous section, we present a case study involving predictions of porosity in the Blackfoot field, Alberta (Township 23, Range 23 W4M). A 3C-3D seismic survey was recorded in October 1995 with the primary target being the Glauconitic member of the Mannville group. The reservoir occurs at a depth of 1550 metres, where Glauconitic sands and shales fill valleys incised into the regional Mannville stratigraphy.

A number of seismic attributes (Chen and Sidney, 1997) are extracted from the P-P seismic volume (Figure 4). Using the model based conversion technique described above, we convert the P-S volume to P-P time (Figure 5) and extract the P-S attributes.

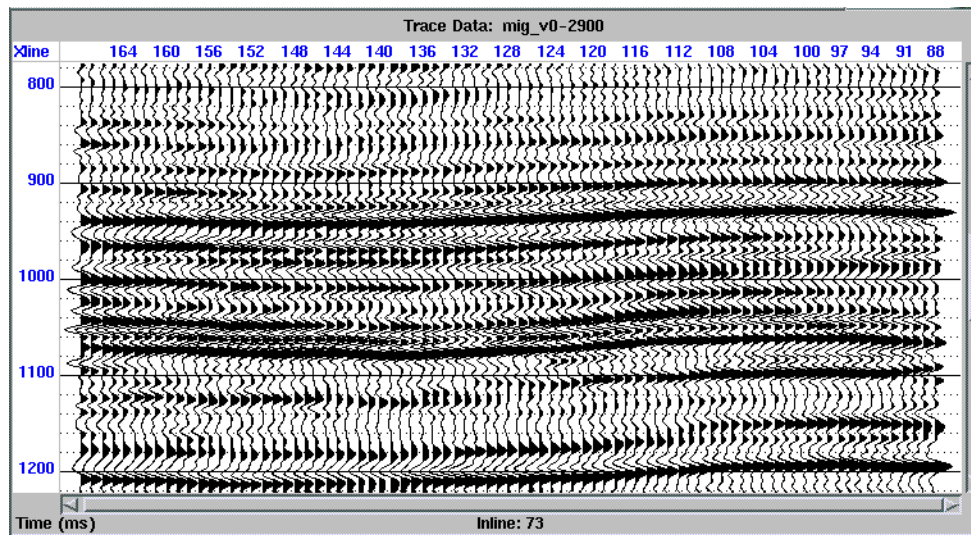


Figure 4: P-P seismic section in the Blackfoot field extracted from the 3-D volume.

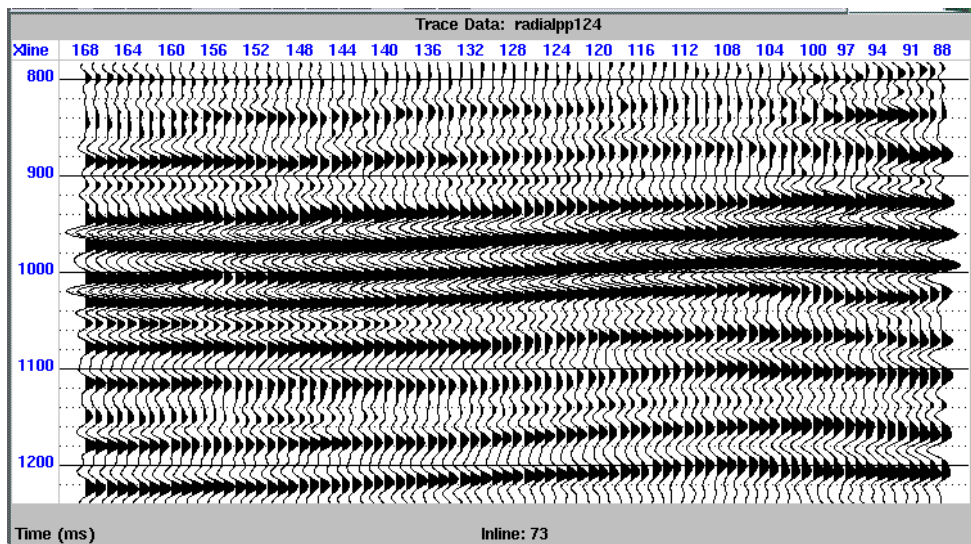


Figure 5: P-S seismic section in P-P time.

Thirteen porosity logs from the covered area are tied with the seismic and converted in time (Figure 6). The red line on the plot shows the chosen time windows to be analyzed.

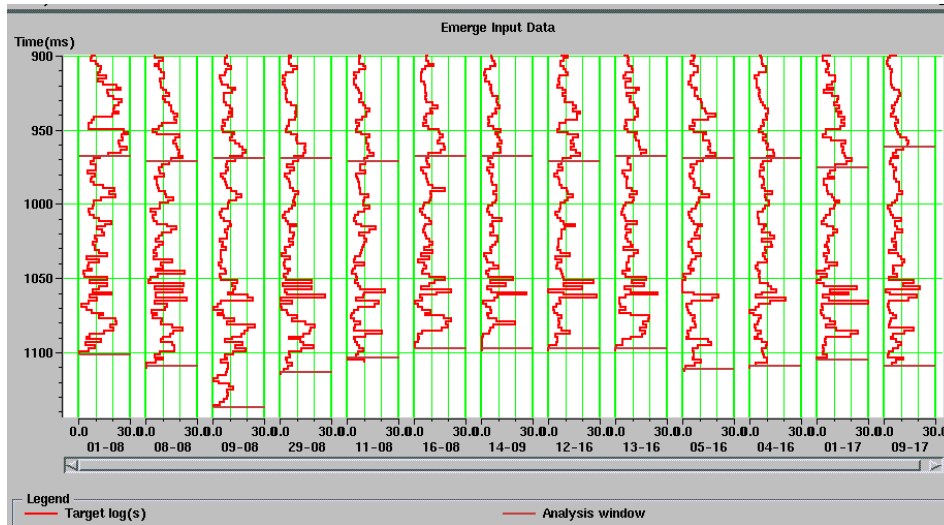


Figure 6: Converted to P-P time porosity logs.

Before applying the method, we have to choose which seismic attributes to use in the analysis. One way to determine the best combination is to qualify the seismic attributes according to their linear correlation with the predicted porosity. However, if there is an inner linear relationship between some of the attributes, the chosen combination may not be the optimal. A better approach is to find the smallest RMS error between the known log and the predicted one from a particular combination of seismic attributes. First the best single attribute is determined, i.e. the attribute with the smallest RMS prediction error - the impedance in this case. Then the impedance is paired with the rest of the attributes and the best pair is found - impedance plus the amplitude envelope (P-P). Then the best triplet is found, impedance, amplitude envelope (P-P), and average frequency (P-P), and so on. Table 1 shows the optimal combination for 8 attributes using a 7-point convolution operator. Note that the shown RMS error corresponds to a combination of the attribute with the ones above it.

Figure 7 is a plot of the average RMS error as a function of the number of seismic attributes used in the multi-regression analysis. The lower black line is the error using all wells in the calculation and the upper red line is called the validation error. It is calculated by averaging the result of 'hiding' or not using a well and predict its values using the others (cross-validation analysis). We see that adding attributes beyond the seventh one did not improve the validation error, so we choose to use the first seven attributes.

Attribute	RMS error
Impedance from inversion (P-P)	3.81
Amplitude Envelope (P-P)	3.55
Average Frequency (P-P)	3.41
Derivative (P-P)	3.34
Dominant Frequency (P-S)	3.28
Amplitude Weighted Phase (P-P)	3.22
Integrated Trace (P-S)	3.16
Integrated Trace (P-P)	3.08

Table 1: Optimal 8-attribute combination. Adding a new attribute to the multi-regression analysis decreases the RMS error. The top seven attributes are ultimately used in the analysis.

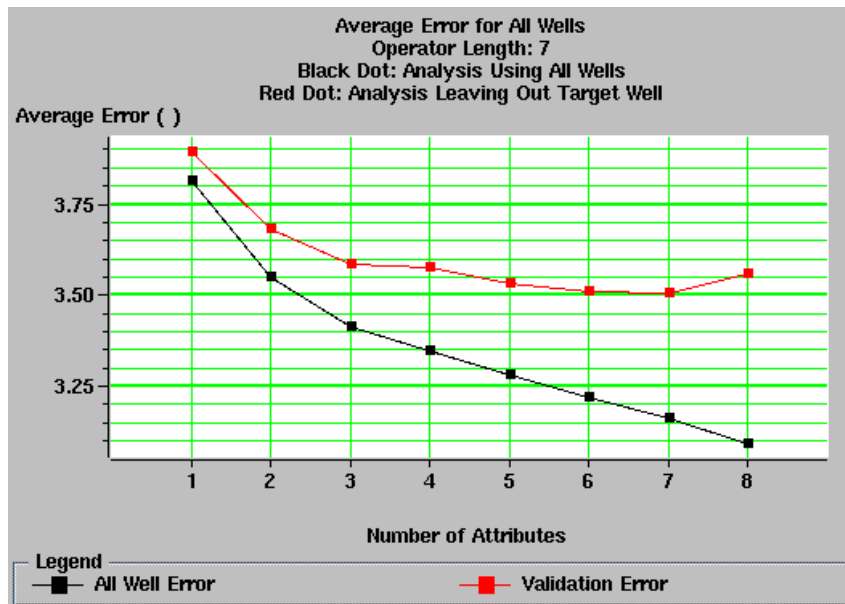


Figure 7: Average RMS error as a function of the number of seismic attributes.

Figure 8 shows the predicted porosity using 7-attribute combination at 01-08, 08-08, and 09-08 well locations. The black curve is the recorded sonic log and the red line is the predicted one. The correlation between the real logs and the predicted ones (for all 13 wells) is 0.76 and the RMS prediction error is 3.16.

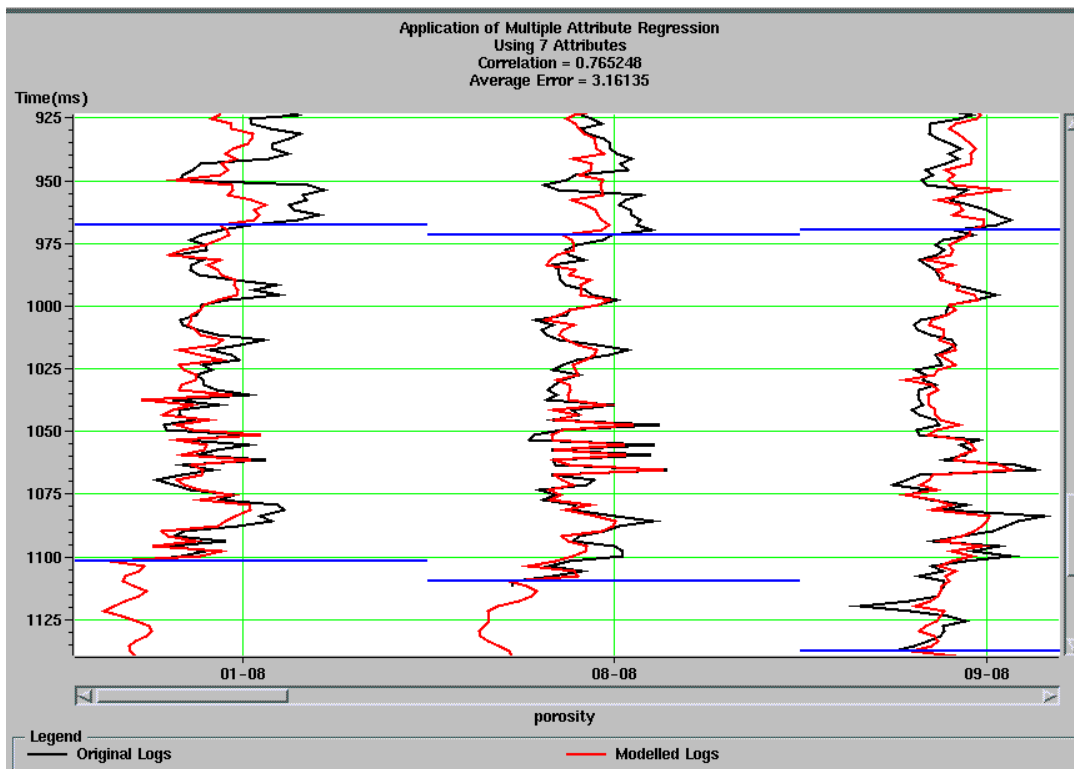


Figure 8: Measured porosity logs, in black, and the predicted one, in red. The correlation is 0.76.

Neural networks are powerful prediction tools, but they should be used with care. The main problem is overfitting of the training data set, which leads to poor prediction on unseen data. To overcome this problem, we divide our data into two data sets: training and testing. The first one is used to train the net and the second one to evaluate its performance. During the training the network builds a nonlinear mathematical model which later is applied to the seismic data to generate a predicted sonic velocity cube.

The training is performed in the following fashion:

- hidden neurons are added one at a time
- training is performed and tested
- construction is stopped when the correlation on the test data shows no further improvement

Table 2 shows the result from the training process using the same seven attributes and a 7-point convolution operator.

Figure 9 shows the recorded porosity logs, in black, and the predicted one, in red, at the 01-08, 08-08, 09-08 well locations.

Data	Correlation	RMS error	Records
All data	0.797	2.96	831
Training	0.803	2.92	581
Test	0.783	3.04	250

Table 2. Results from the neural network training.

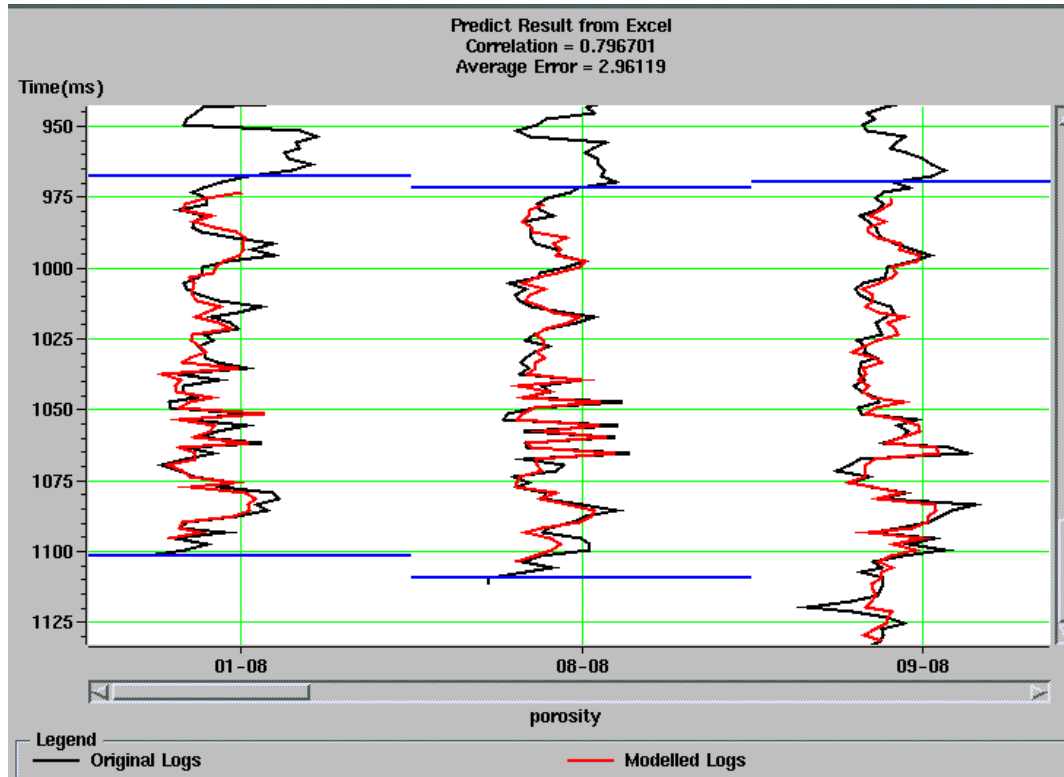


Figure 9: Measured porosity logs, in black, and the predicted ones from the neural network, in red. The correlation is 0.80.

The derived relationship from the multi-regression analysis and the neural network are applied to the seismic data set and a predicted porosity cubes are generated . Figure 10 and Figure 11 are cross-sections of the porosity cubes at the 09-08 well location (oil well). The high porosity anomaly is interpreted as a sand channel. Figure 12 and Figure 13 are porosity slices at top of the channel picked horizon plus 4 ms. The high porosity anomaly correlates very well with the producing oil wells in the area.

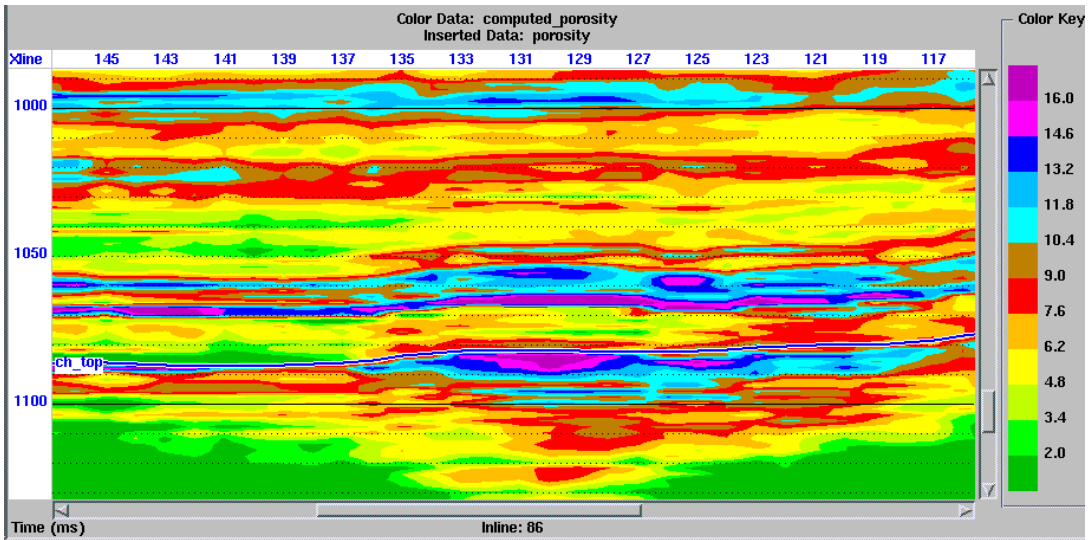


Figure 10: Predicted porosity from multi-regression analysis using 7 attributes and 7-point convolution operator.

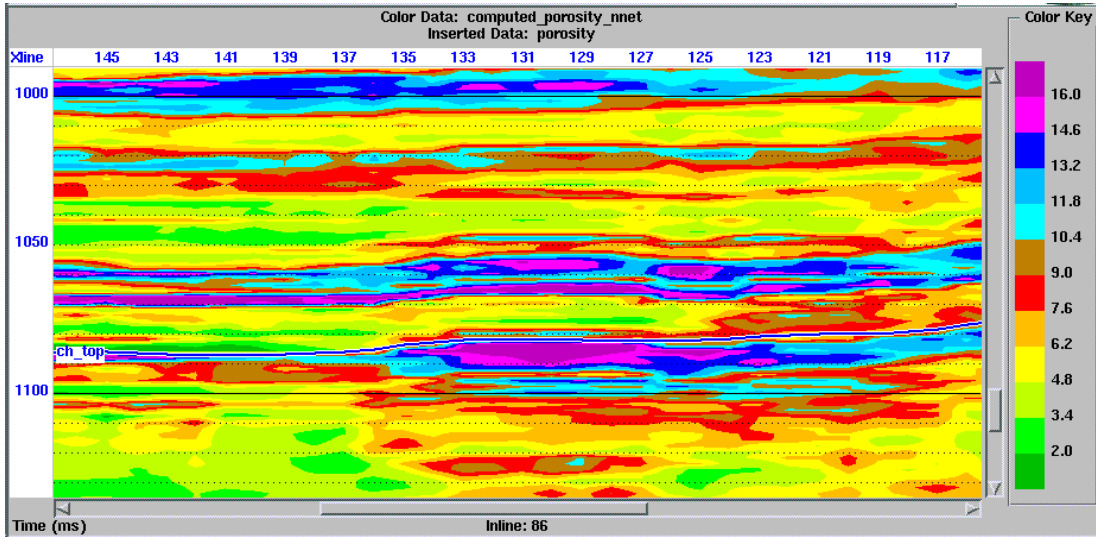


Figure 11: Predicted porosity using neural network.

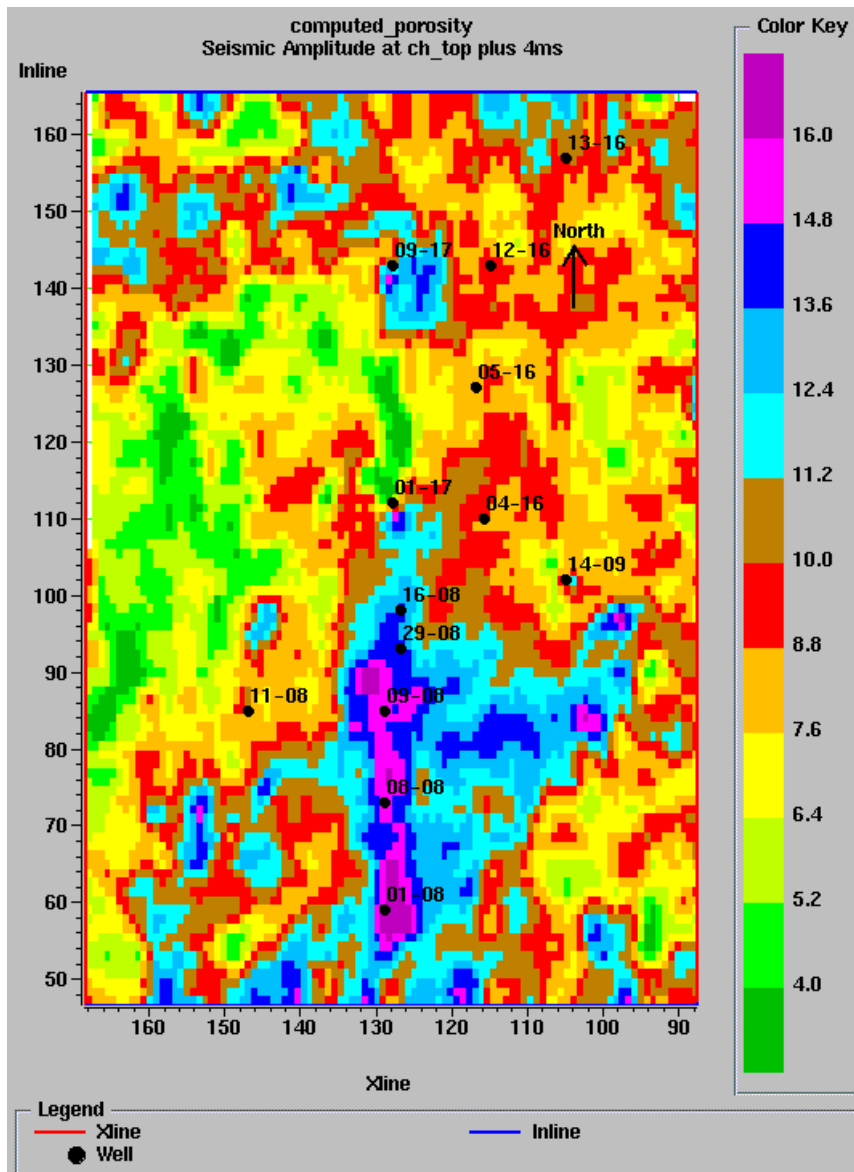


Figure 12: Porosity data slice, top of the channel horizon +4 ms, using multi-regression analysis.

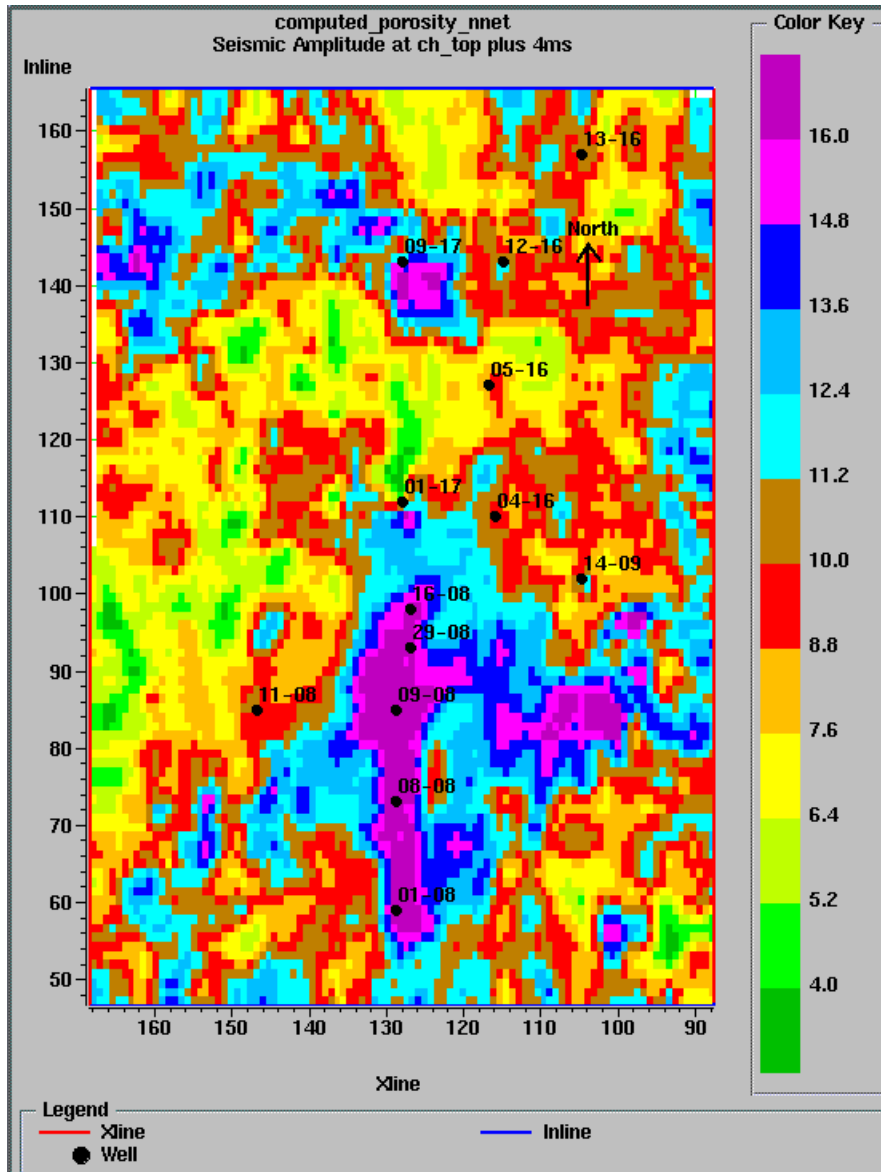


Figure 13: Porosity data slice, top of the channel horizon +4 ms, using neural network.

CONCLUSIONS

Multi-regression analysis and neural networks can be successfully used to predict log properties from seismic attributes. Both P-P and P-S information is useful in log prediction as evidenced by the type of the optimal attributes. In the present example, the predicted logs showed high correlation of 0.76 using multi-regression analysis and 0.80 using neural network as a prediction tool. The generated porosity cubes show similar high porosity anomalies that correlate well with the producing oil wells in the area.

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