Sonic log predictions using seismic attributes

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ABSTRACT

Deriving a deterministic relationship between the seismic data and geological properties of the subsurface is a difficult task. Using multi-regression analysis and neural networks, we derive statistical rather than theoretical relationships. The relationship is found at the well locations and applied to the exploration area covered by seismic data.

Nine well locations in the Blackfoot area, Alberta, are used to derive relationships between the measured sonic velocity and seismic attributes. Cross-validation tests are used to determine the quality of the derived relationships. Using a neural network we achieved the highest correlation between the measured and the predicted sonic logs: 0.87. 3-D sonic velocity volumes are generated and a low-velocity anomaly is interpreted as a sand channel.

INTRODUCTION

Seismic data are often successfully used to derive structural information about the subsurface and hopefully locate hydrocarbon traps. Deriving rock and reservoir properties from the seismic data is another challenging task. A traditional approach is to look for a theoretical relationship between the physical parameter and some seismic attributes. For example, low impedance gas sands can cause anomalous impedance contrasts that lead to bright spots. Another deterministic approach uses amplitude-versus-offset (AVO) effects to find Poisson's ratio anomalies. However, the relationship between the physical parameter and the seismic attributes might not be obvious. Another pitfall is that the deterministic relationships are general and might not be appropriate for a particular area. To overcome the problem, we choose to derive statistical, rather than deterministic relationships. The approach is called data-driven methodology (Schultz at al., 1994).

In this article, we discuss two methods, linear multi-regression analysis and neural networks, which combine a well log property and seismic attributes to predict property distributions. A field data example from the Blackfoot area, Alberta, is presented. Nine sonic logs are used to find the relationship between the sonic velocity and seismic attributes. Once found, it is applied to a 3-D seismic volume. The final result is a 3-D volume, whose traces are predicted sonic logs. The "Emerge" software package from Hampson-Russell Software Services Ltd. and the "Predict" neural network program from NeuralWare Inc. are used in the current work.

1 Hampson-Russell Software Services Ltd.

METHODOLOGY

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

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

where:

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

$F[\ldots]$ – functional relationship

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

The functional relationship can be found using linear multi-regression analysis. For N measured log property points, we have:

$$P_1 = W_1A_{11} + W_2A_{21} + \ldots + W_MA_{M1} + W_{M+1}$$

$$P_2 = W_1A_{12} + W_2A_{22} + \ldots + W_MA_{M2} + W_{M+1}$$

$$\ldots$$

$$P_N = W_1A_{1N} + W_2A_{2N} + \ldots + W_MA_{MN} + W_{M+1}$$

In matrix form:

$$\mathbf{P} = \mathbf{WA}$$

The weight matrix **W** is found by least-squares optimization.

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 property. 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 parameter and the predicted one from a particular combination of seismic attributes. Using this criterion, we may determine the optimal combination of seismic attributes for prediction of a particular log property.

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

$$P_1 = W_1 * A_1 + W_2 * A_2 + \ldots + W_M * A_M + W_{M+1}$$

$$P_2 = W_1 * A_1 + W_1 * A_2 + \ldots + W_M * A_M + W_{M+1}$$

$$\ldots$$

$$P_N = W_1 * A_1 + W_2 * A_2 + \ldots + W_M * A_M + W_{M+1}$$

where:

W_i – convolution operator, i = 1, …,M.

W_{M+1} - constant

In a case of an L-point convolution operator there are L • M unknown weights to be determine by the least-squares optimization. The discussed method can perform well if the functional relationships between the predicted log property and the seismic attributes are linear. In the case of nonlinear relationships, we may use neural networks as a prediction tool based on nonlinear optimization techniques.

Figure 1 shows schematically the basic architecture of a multilayer feedforward neural network. It consists of a set of neurons that are arranged into two or more layers. There is an input layer and an output layer, each containing at least one neuron. Between them there are one or more “hidden” 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. In the example shown in Figure 1, we have four inputs (four seismic attributes: A1, A2, A3, A4), one hidden layer containing three neurons and an output neuron (representing the predicted log property). The number of connections is 15, i.e. 15 weights. A neuron is characterized by the weights, which multiply each input, and an activation function, which is applied to the weighted sum of the inputs in order to produce the neuron’s output. Mathematically the process is written as:

$$\text{neuron's output} = f\left(\sum_{i=0}^{n-1} x_i w_i + w_n\right)$$

where:

w_i – connection weights (w_n is a constant called bias)

x_i – neuron inputs

f – activation function, usually the sigmoid function

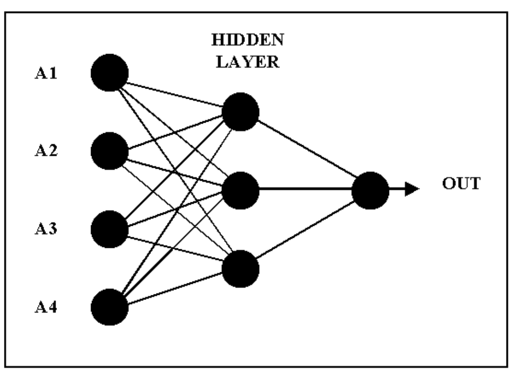

Figure 1: Basic neural network architecture.

A 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 data set is required and the weights are modified iteratively so that the outputs of the network match closely the target outputs.

BLACKFOOT FIELD EXAMPLE

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

Nine sonic logs from the covered area are tied with the seismic and converted to time (Figure 2). The red line on the plot shows the chosen time windows.

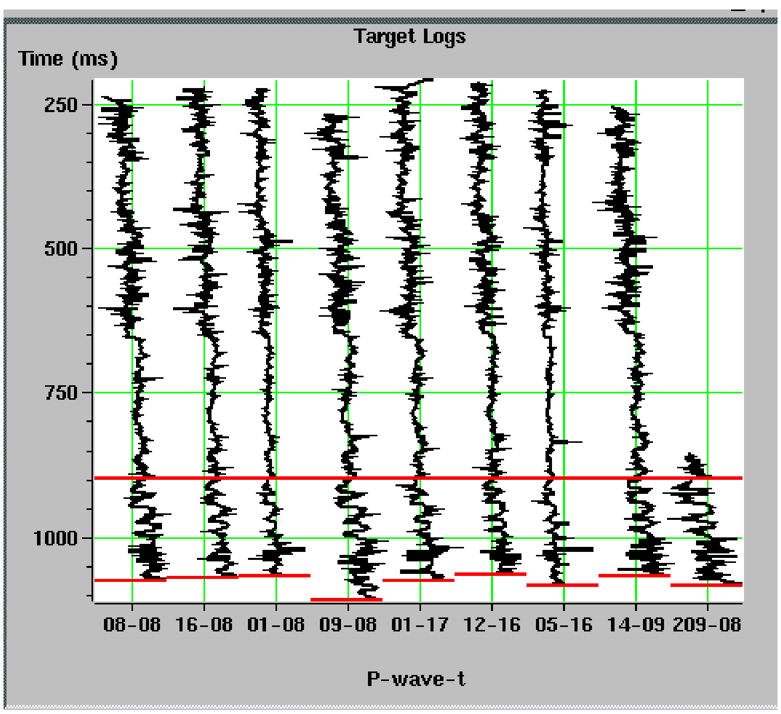

Figure 2: Measured sonic logs in the Blackfoot area.

A number of seismic attributes (Chen and Sidney, 1997) are extracted from the seismic volume and cross-plotted with the sonic log samples over the chosen window. Table 1 shows some of the extracted attributes, their correlation with the sonic velocity, and the RMS prediction error between the real log and the predicted one using a particular attribute. The time has the highest correlation (showing a general trend of sonic velocity increase with time), the next one is the inverted seismic trace, integrated absolute amplitude, and so on.

Attribute	RMS error (m/s)	Correlation
Time	349.7	0.517
Inverted trace	354.6	0.497
Integrated absolute amplitude	398.8	0.218
Amplitude weighted phase	399.5	0.211
Derivative	400.6	-0.197
Instantaneous phase	400.7	0.196
Integrate	403.1	0.164
Dominant frequency	403.8	0.153
Average frequency	403.9	0.152
Cosine instantaneos phase	406.2	-0.110

Table 1: Seismic attributes showing the best correlation with the sonic logs.

Table 2 shows the optimal 8-attribute combination as a result from multi-regression analysis. First, the best single attribute is determined (time), then the best pair of attributes (time and inverted seismic trace), then the best triplet and so on. Note that the order in Table 2 is not the same as in Table 1. At this point we have to answer the question: How many attributes should we use in the prediction process? Adding more attributes may lead to overpredicting, i.e. predicting the noise in the sonic logs.

Figure 3 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 RMS prediction error using all wells in the calculation. The upper red line is called validation error. It is calculated by averaging the result of “hiding” a well and predicting its value using the rest (cross-validation analysis). The red line is used to make the decision how many attributes to use in the prediction process. Obviously adding the attributes beyond the 5-th one did not decrease the validation error, so we choose to use the first 5 attributes.

Figure 4 shows the cross-validation test using the optimal 5-attribute combination at 09-08, 01-17, and 12-16 locations. The measured sonic logs are plotted in black and the predicted one is plotted in red. The average correlation between the predicted logs and the measured logs for all nine well locations in the area is 0.64 and the average RMS error is 313 m/s.

Attribute	RMS error (m/s)
Time	347.7
Inverted trace	323.2
Cosine instantaneous phase	318.9
Amplitude envelope	314.2
Instantaneous frequency	310.2
Average frequency	308.8
Second derivative	307.8
Instantaneous phase	307.3

Table 2: Optimal 8-attributte combination.

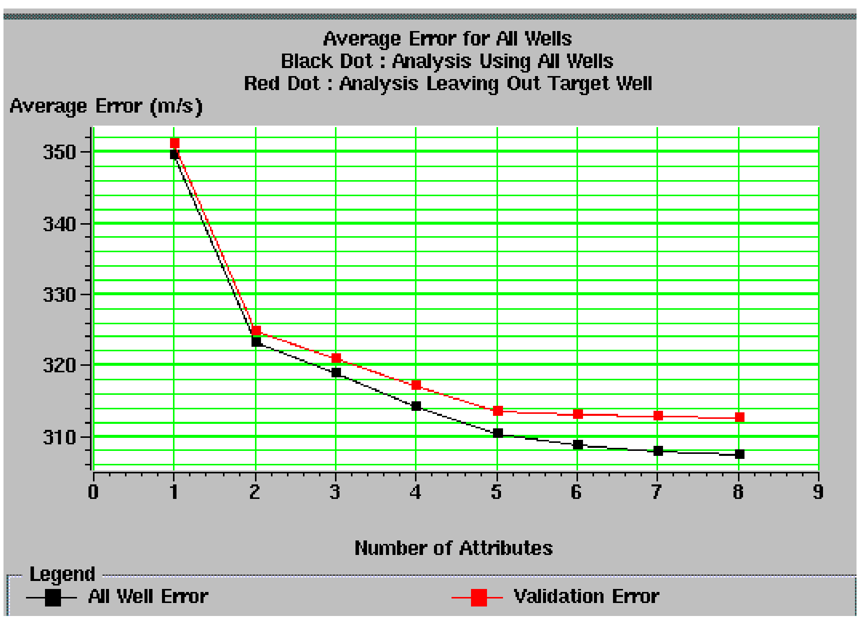

Figure3: RMS average error vs number of seismic attributes.

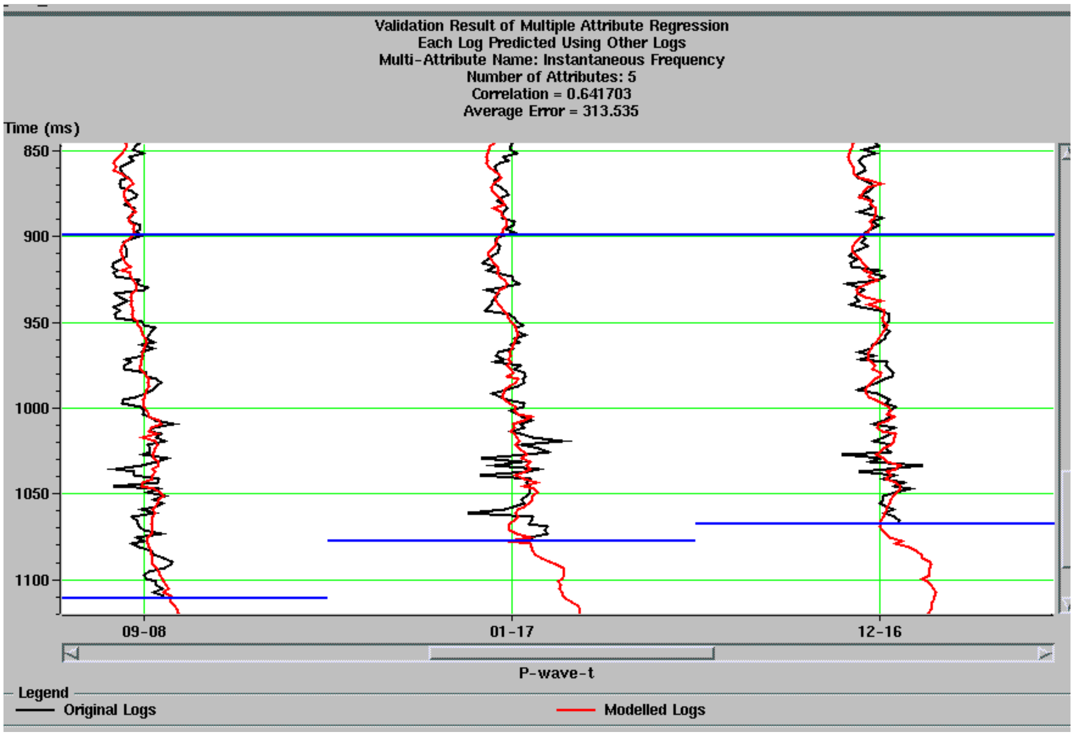

Figure 4: Measured logs (in black) and predicted logs (in red).

The same analysis was performed using a 9-point convolution operator with a 4-point lag. Table 3 shows the optimal 8-attribute combination .

Figure 5 is a plot of the average RMS velocity as a function of the number of seismic attributes used in the analysis. The first 5 attributes were chosen for the prediction process. Note that by adding the 6-th attribute, we actually increase the validation error.

Figure 6 shows the cross-validation test using the optimal 5-attribute combination at 09-08, 01-17, and 12-16 well locations. The measured sonic logs are plotted in black and the predicted ones are plotted in red. The average correlation between the nine predicted logs and the real ones is 0.76 and the average RMS error is 267 m/s.

Attribute	RMS error (m/s)
Inverted trace	343.1
Amplitude weighted cosine phase	310.9
Time	269.7
Cosine instantaneous phase	253.9
Average frequency	248.6
Amplitude envelop	243.7
Amplitude weighted frequency	239.4
Instantaneous frequency	234.6

Table 3: Optimal 8-attribute combination using a 9-point convolution operator.

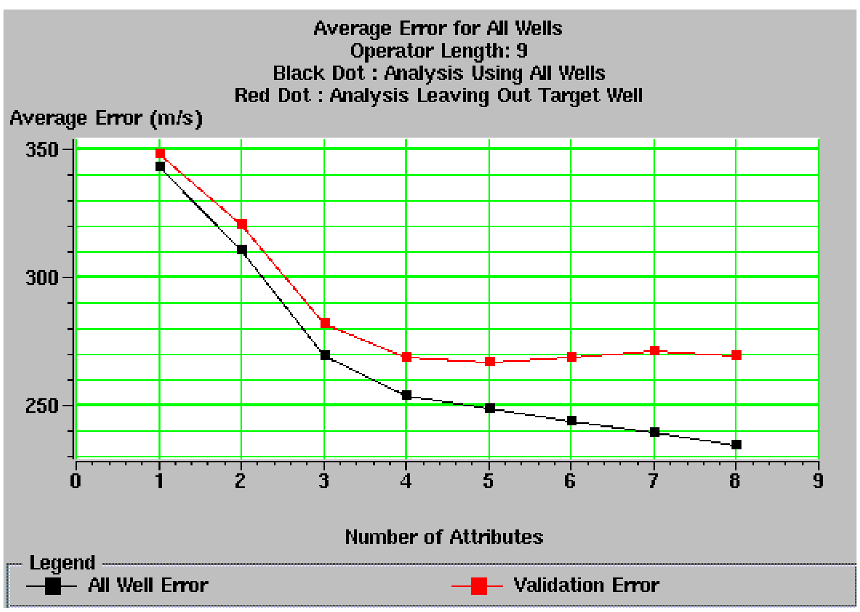

Figure 5: RMS average error vs number of seismic attributes using a convolution operator.

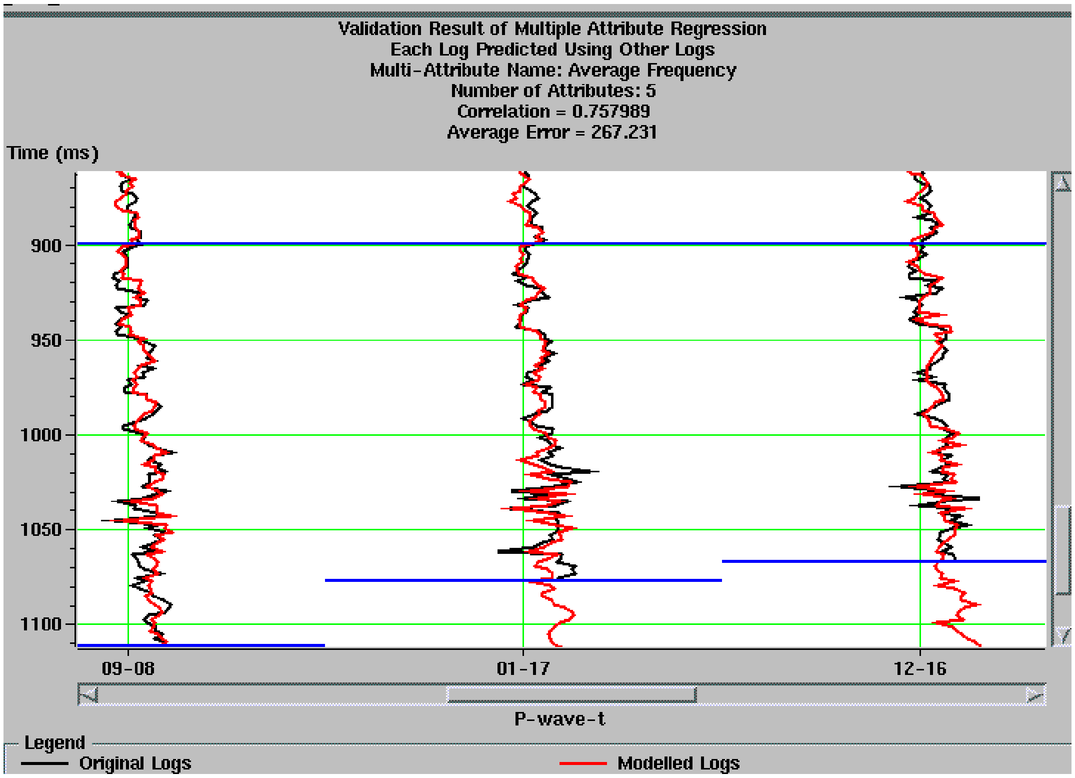

Figure 6: Measured logs (in black) and predicted logs (in red) using convolution operator.

The next step in our analysis is to apply a neural network. Neural networks are very powerful tools, but should be used with care. The main pitfall is to overteach, i.e. to train the network to predict the very fine details in the training set. In the case of noisy data, this could lead to significant errors. One way to overcome the problem is to divide the available data into training and testing data sets. The training data set is used to train the network and the testing data set is used to evaluate its performance.

In the current case, the result from the multi-regression analysis with a 9-point convolution operator is used to train the network. The total number of cases (the number of measured log samples), 748, is divided into training data set, 523 cases, and testing data set, 225 cases (30%). The structure of the neural network is: 45 inputs, 9 neurons in the "hidden" layer, and 1 output. Table 4 shows the results from the training process.

Figure 7 is a plot showing the application of the trained network at the well locations 09-08, 01-17, and 12-16. The real logs are shown in black and the predicted ones in red. The average correlation is 0.87 and the average RMS error is 204 m/s.

Data	Correlation	RMS error	Records
All	0.87	196	748
Train	0.89	183	523
Test	0.83	223	225

Table 4: Results from the neural network training.

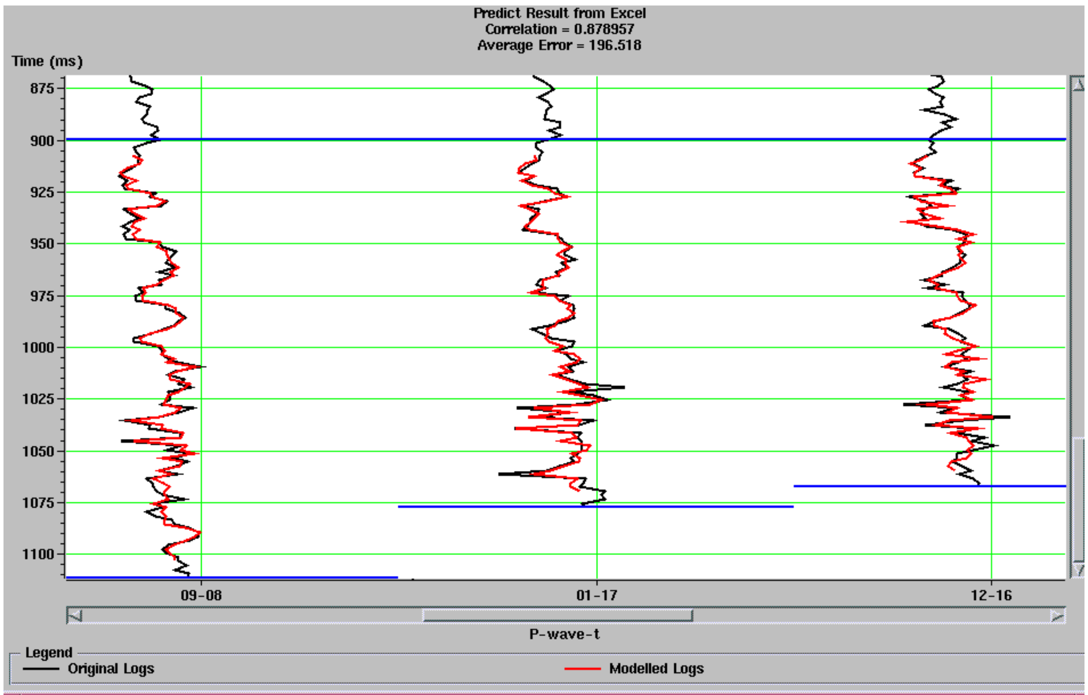

Figure 7: Measured logs (in black) and predicted logs (in red) using a neural network.

The derived functional relationships from the three techniques are applied to the 3-D seismic volume and three 3-D velocity models are generated. Figures 8, 9, and 10 are plots of inline 96 extracted from the volumes. It crosses the producing oil well 08-08 at CDP number 124. The low-velocity anomalies around 1070 ms are interpreted as sand bodies. Note the higher resolution in Figures 9 and 10 compared with Figure 8.

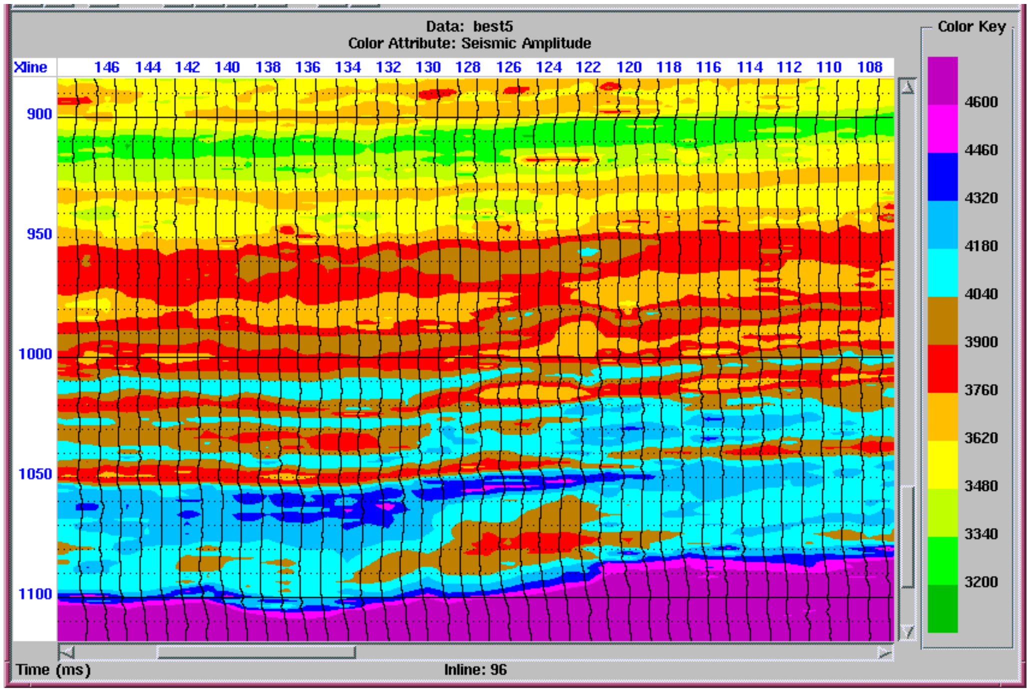

Figure 8: Sonic model using 5 attributes, inline 96.

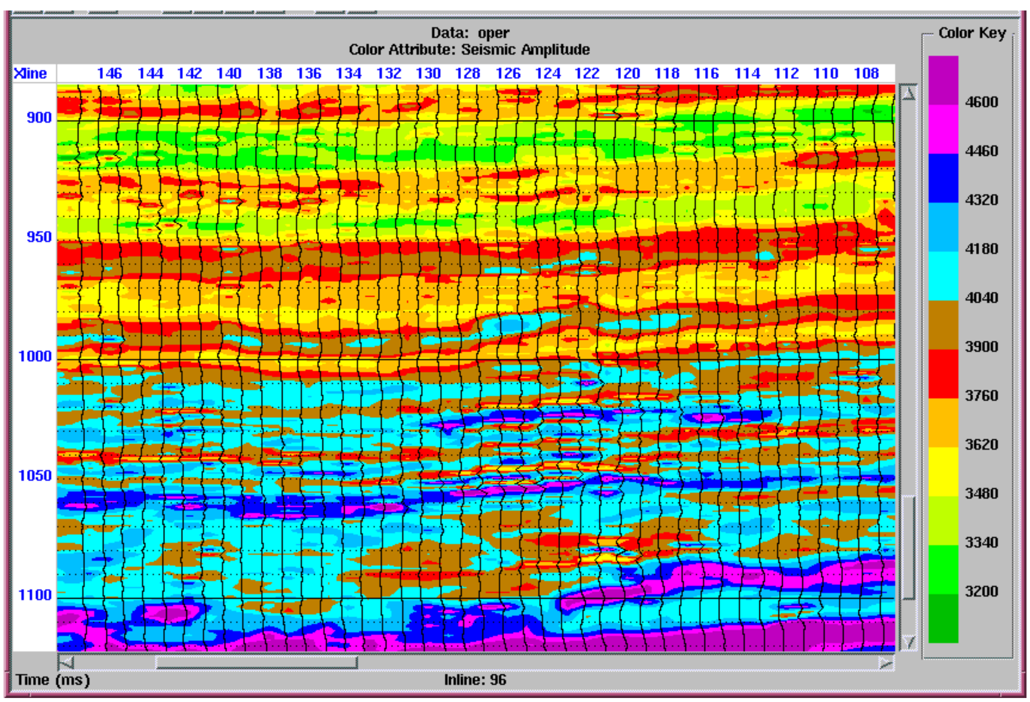

Figure 9: Sonic model using 5 attributes and a 9-point convolution operator, inline 96.

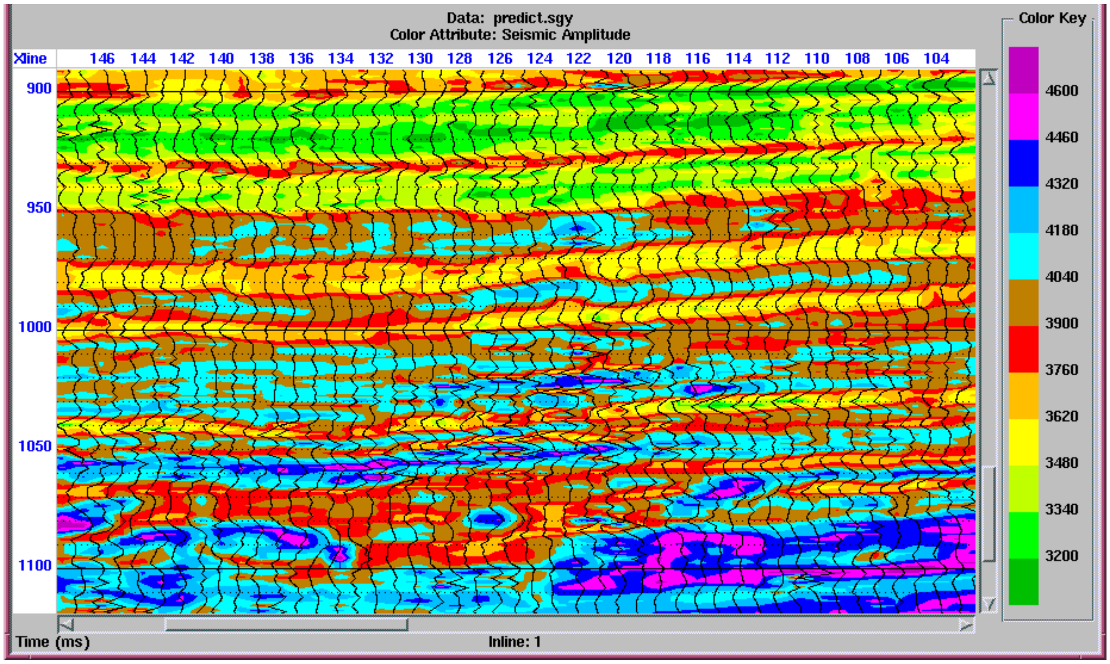

Figure 10: Sonic model using neural network, inline 96.

CONCLUSIONS

Linear multi-regression analysis and neural networks can be used successfully to derive log properties from seismic attributes. Cross-validation tests used to evaluate the predicting process showed good correlation between the predicted model and the measured log property – sonic velocity. Using convolutional operators instead of constant weights improved the cross-validation correlation by 11%. Using neural network as a prediction tool we achieved the highest correlation: 0.87.

ACKNOWLEDGEMENT

The authors would like to thank the CREWES sponsors for their support.

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