Well log estimates and confidence intervals by using artificial neural networks

Rafael E. Banchs & Reinaldo J. Michelena, PDVSA-Intevep*

Summary

Estimation of petrophysical properties of rocks from seismic attributes plays a very important role in defining reservoir models for reservoir characterization and simulation. However, some degree of uncertainty is always related to such property estimates. This work presents a nonlinear analysis technique, based on artificial neural networks, for dealing with the problem of seismic-guide well log estimation and its related uncertainties. Field data examples demonstrate the potential of the method.

Introduction

Indirect estimation of petrophysical properties from other available sources of information, such as well logs and seismic data, plays a very important role in reservoir characterization and simulation. Recently, neural network based methods for estimating rock properties from seismic attributes have been gaining some popularity (Shuki et all, 1994; Todorov et all, 1997 and 1998). The main advantage of neural networks over other estimation methods is their ability for extracting nonlinear relationships among data sets.

However, these neural-net estimation methods do not give any information about the confidence intervals associated with the resulting estimates. Since it is always desirable to estimate also confidence intervals for a given property estimate, stochastic methods are generally used in order to quantify the uncertainties associated to the obtained estimates (Deutsch and Journel, 1992).

In the present work, we show a neural network-based method for estimating well logs, as well as the associated confidence intervals, using *3D* seismic attributes as a guide. First, the methodology and some practical issues related to its implementation are briefly discussed. Then, a field data example is shown, in which a volume of spontaneous potential and the corresponding uncertainties in the estimation process are estimated from the seismic attributes of a *3D* volume.

Data adjustment and re-sampling

The first problem encountered when implementing the estimation technique is that the input data set (seismic attributes) and the output data set (well logs) are measured in two different domains, time and depth, respectively. The availability of some velocity information, which allows the conversion of the well log data to time, is required. When having the appropriate T-Z curves, the depth to time conversion of the data is easily achieved by using spline interpolators.

A second problem is the difference in resolution between the seismic data and the well log data. Due to this problem, a resolution adjustment is required. In order to avoid affecting convergence during the training stage of the neural network, it is recommended to low-pass filter the well log data according to the spectral content of the seismic data. As a result of this low-pass filtering the proposed technique is limited to estimate the desired information at the resolution of the seismic wavefield.

Another problem results from the difference between the sampling rates of seismic data and well log data. Then, well log data has to be down-sampled (or seismic data up-sampled, or both) in order to obtain a set of input-output sample pairs for training the neural network. The up-sampling and down-sampling of the data sets can be performed directly in the discrete domain by using conventional re-sampling schemes (Oppenheim and Schafer, 1989).

Averaging and attribute computation

The previous section discussed the problems arising when trying to match the seismic and petrophysical data in the time (vertical) dimension. Matching both data sets in the horizontal spatial coordinates, in-line and cross-line, also has its implications. Since the influence of medium properties in a given seismic trace depends on CDP, bin size and Fresnel zone; a given well must be related to a group of traces instead of to a single one. In this way, an average trace, which has been computed by averaging the associated group of traces, is used for the computation of the seismic attributes.

A final important issue to be considered is the selection of the seismic attributes to be used. The optimal set of seismic attributes to be used for estimating an specific property must be determined empirically since the relationships between attributes and properties usually change from one site to another. Among the most commonly used are amplitude, derivative of the amplitude and second derivative, integrate of the amplitude, instantaneous frequency, instantaneous phase and average frequency (Taner, 1976).

Estimation of confidence intervals

In order to compute, or estimate, confidence intervals for the estimated well log volume an statistical analysis has to be performed on the problem's model space. Then, the estimation algorithm must be used several times to obtain a representative number of samples of the model space that allows to infer a distribution and compute its parameters (Breiman, 1973).

Well log estimates and confidence intervals

Each time the neural network is trained and then used to compute an estimate, an independent sample of the model space is obtained. After a representative amount of simulations, histograms for each point in the volume can be computed.

Although, strictly speaking, a very large amount of simulations are required (which makes the procedure very expensive from a computational point of view), an approximate study can be performed by using a moderate amount of simulations.

The obtained distributions can be considered to be normal. In this manner, a mean value estimate and its standard deviation are computed, from which a relative error, or confidence interval, can be obtained.

It is important to notice that this analysis only provides information about the consistency of the estimation but not about its bias. In fact, the bias of the estimation can be only verified at the training locations, where the actual well log information is known. Nevertheless, estimates for the bias across the whole volume can be computed by using the biases measured at wells and the same artificial neural network technique described before.

Field data example

In this section, the methodology proposed above is used to estimate a volume of well log data from the attributes of a *3D* seismic volume from eastern Venezuela. In the particular example presented here, it is intended to estimate spontaneous potential (SP) logs, which are typically used as lithological indicators.

Input data and simulation parameters

Figure 1 illustrates the region of the field under consideration, as well as all well locations used for training the algorithm. The total extension of the area under consideration is 5.73 Km^2. The time interval considered ranges from 1.6 s to 1.7 s.

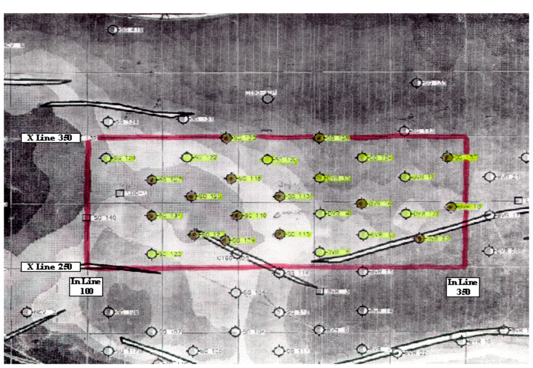

Fig. 1: Region under consideration and well locations.

A total amount of 25 spontaneous potential logs were used for training the neural network, which was a four layer perceptron with 10, 12, 12 and 1 neurons en each layer, respectively. The back propagation algorithm was used for training the neural network (Haykin, 1994).

Ten attributes were used in this experiment; such attributes were the number of sample, in-line coordinate, cross-line coordinate, integral of the amplitude, integral of the absolute amplitude, instantaneous phase, derivative, second derivative, average frequency and average amplitude. The number of neurons for each layer and the seismic attributes were empirically selected after some experimentation.

Simulations and results

A total of 70 simulations were performed. So, a total of 70 estimated SP volumes where obtained, for which distributions were observed and statistics were computed. Figures 2, 3 and 4 present the average SP, its standard deviation and relative error, respectively, for a line that crosses the locations of wells A, B and C.

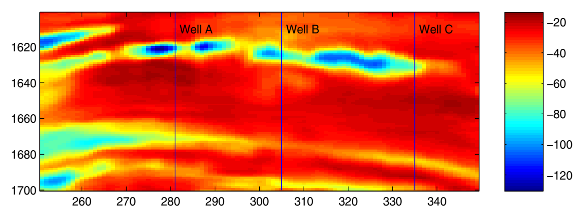

Fig. 2: Average SP section extracted from the *3D* volume.

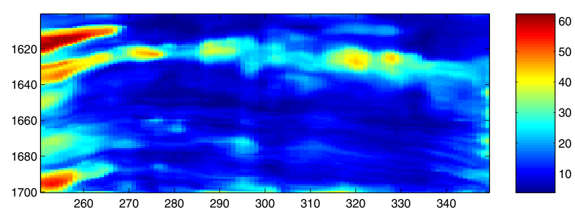

Fig. 3: Standard deviation section.

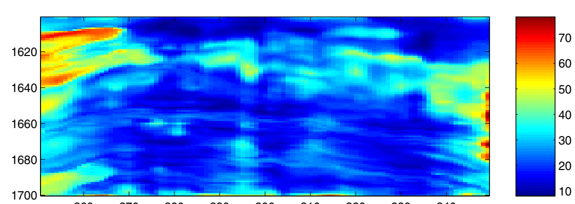

Fig. 4: Relative error section.

Figure 5 shows the low-pass filtered versions of the actual SP curves and the average of the 70 estimated SP curves at the three wells shown in figure 2.

It can be seen from the figure how the estimated curves adjust to the actual curves. The correlation coefficients obtained for the actual and estimated *SP* curves at wells *A*, *B* and *C*, were 0.92, 0.83 and 0.72, respectively.

Notice also from figure 4 that the largest relative error values occur at the borders of the section. This suggests that the estimation technique performs better when interpolating than when extrapolating. This proves the fact that the availability of enough well data is of critical importance for the success of the method.

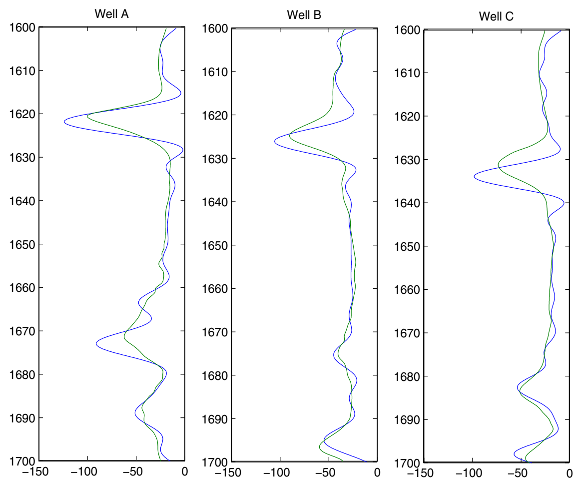

Fig. 5: Actual (blue) and estimated (green) *SP* values at well locations *A*, *B* and *C*.

Conclusions

The proposed methodology provides a good approach for estimating petrophysical properties and/or well log data from seismic attributes, as well as the consistency of such estimates, which allows the computation of relative errors. These error values give a good idea of the confidence intervals associated to property maps. Also, different from the conventional linear regression techniques, this method is able to infer the nonlinear relationships existent between well logs and seismic data.

Nevertheless some important considerations have to be taken in to account when dealing with this kind of procedure:

- The depth to time conversion of well log data is a very critical step. For this reason, accurate T-Z curves are required.
- The resolution of the resulting estimates are limited by the seismic data; i.e. the resolution of the estimated well logs will depend on the frequency content of the processed seismic wavefield. However, more research needs to be done to incorporate into the estimation high resolution information contained in the well logs.
- Although very expensive from a computational point of view, the computation of confidence intervals provides useful information for interpreting the resulting well log estimates.

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