Petrophysical Estimation from Seismic Attributes by Using Artificial Neural Networks

Rafael Banchs & Reinaldo Michelena, PDVSA-Intevep

Summary

Estimation of the petrophysical properties of rocks from seismic attributes plays a very important role in defining reservoir models for reservoir characterization and simulation. This work presents a non linear analysis technique, which is based on neural networks, for dealing with the problem of petrophysical property estimation by using seismic attributes. Some synthetic simulations and experimental results are also presented.

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. Two problems must be distinguished, the problem of property estimation at well locations and the problem of property interpolation in the rest of the region. In the second one, petrophysical properties in all the volume are obtained by interpolating the known property values at the well locations.

Recently, neural network based methods for estimating rock properties from seismic attributes have been gaining some popularity (Todorov *et all*, 1997 and 1998). The main advantage of neural networks over conventional property estimation methods is their ability for extracting non-linear relationships among data sets.

In the present work, we describe a technique that uses a neural network to estimate lithology from seismic attributes. First, two synthetic simulations are presented. In the synthetic examples, two velocity models, one with structural variations and the other with stratigraphic variations, are used for generating synthetic seismic sections from which the velocity fields are recovered by using the proposed technique. Then, some experimental results from a field in eastern Venezuela are shown. In these experimental results, a volume of spontaneous potential is estimated from the seismic attributes of a *3D* volume.

Well Data Conversion to Time

The first problem encountered when try to implement the estimation technique is that the input data set (seismic attributes), and the output data set (properties) are measured in two different domains, time and depth, respectively. For this reason, it is required the availability of some velocity information. This information allows the conversion of the well data to time in order to make it possible for the neural network to infer the relationships in a coherent way. The problem with this kind of information is that it is in most of the cases imprecise. It would be ideal the availability of a T-Z curve for each well location that is going to be used for training the algorithm. When this is not possible, a regional T-Z curve has to be used.

When having the appropriate curves, the depth to time conversion of the well data is easily achieved by using spline interpolators.

Resolution Adjustment and Re-Sampling

Due to the difference in resolution between the seismic data and the well information a resolution adjustment is required. It is well known that well information is much more resolutive than seismic data; so the actual problem is that the proposed technique intends to estimate a high resolution data set from a low resolution data set, which is obviously not possible.

In order to avoid affecting convergence during the training stage of the neural network, it is recommended to low-pass filter the well 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 petrophysical properties at the resolution of the seismic wavefield.

---

*Although this has been proven to work effectively, the effects of using the well data set with its full resolution during the training stage have not been studied yet.

Another problem is the one related to the fact that different sampling intervals are always used when acquiring seismic data from when recording well data. Then, in addition to convert well data from depth to time and adjust its resolution to the one of the seismic data, well data have to be down-sampled (or seismic data have to be up-sampled, or both). This must be done in order to obtain a set of input-output sample pairs for training the neural network (training set). 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 & Schafer, 1989).

Seismic Averaging and Attribute Computation

The previous sections discussed the problems arising when trying to match the seismic and well data in the time (depth) dimension. Matching seismic and well data in the horizontal spatial coordinates, in-line and cross-line, also has its implications. Since the spatial location of traces in a migrated seismic volume is actually related to the concepts of *CDP* and *Bin size*, it would be a mistake to associate a single trace to a given well. Actually, a given well must be associated 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 existing between attributes and properties are variable depending on the type of geology, frequency content and stratigraphy, among others. Among the most commonly used are amplitude, derivative, second derivative, integrate, instantaneous frequency, instantaneous phase and average frequency (Taner, 1976).

Neural Network Training Strategies

Although convergence of the weight matrix during the training process and the resulting performance of the neural network depends on a multitude of factors, such as the amount of layers and neurons, kind of activation function and quality and amount of the available data; there are some algorithmic factors that can help to improve the performance of the neural network. In this section, three important considerations related to the practical implementation of the neural network algorithm are discussed (Haykin, 1994).

- *Input Variable Normalization.* Large differences among the dynamical ranges of the input variables can make unstable the training process. For this reason, all the input variables must be normalized to a given range such as $[0, -1]$. The variability of the dynamical range for each variable over the whole problem space must be evaluated in order to select the appropriate normalization factors.

- *Linearized Output Layer.* In order to avoid saturation of the neural network's outputs, no activation function must be defined at the output layer neurons. In this way, each neuron at the output layer behaves as a linear combiner of the previous layer outputs.

- *Training Set Selection.* Two data sets must be created from the available petrophysical information, a training set and a test set. While the training set is the one used to actually train the neural network (Haykin, 1994), the test set is used to determine when to stop training. After each epoch[†], the total error over the test set must be computed and the training must be stopped when this error reaches its minimum. If training is continued, the network looses its generalization ability. In general, the training and the test sets are selected at random over the available data in a ratio of $2:1$, respectively.

Synthetic Data Simulations

In this section, the proposed methodology is tested with two synthetic data sets computed from two

[†]An epoch refers to a period of training in which the whole training set has been presented to the network.

different velocity models. The first data set is derived from a 2D velocity model with structural variations, and the second one is derived from a 2D velocity model with stratigraphic variations.

MODEL AND SIMULATION PARAMETERS The structural model consists on seven non-flat layers of constant velocity with a total horizontal extension of 61 distance units and a vertical extension of 1000 time units. This model is illustrated in the upper half of figure 1. The stratigraphic model, on the other hand, consists on seven flat horizontal layers with lateral velocity gradients. It is illustrated in the upper half of figure 2. The stratigraphic model has the same extension as the structural one‡.

The neural network architecture used was a four layer perceptron (input layer, two hidden layers and output layer), with 8, 10, 8 and 1 neurons, respectively, which was trained by using the back propagation algorithm. Eight seismic attributes were used in the simulations, they are the number of sample, horizontal coordinate, amplitude, amplitude derivative, instantaneous phase, average frequency, integral of the absolute amplitude and average amplitude. Both, the number of neurons in each layer and the attributes used, were selected empirically after some experimentation.

SIMULATIONS AND RESULTS Three different simulations were performed. In simulation A, the structural model was used and the neural network was trained at position 1 in the horizontal direction. Figure 1 shows the original and the estimated velocity models for this simulation. As seen from figure 1, the neural network was able to reconstruct the original velocity model.

In simulation B, the stratigraphic model was used and the neural network was trained at position 1 in the horizontal direction. Figure 2 shows the original and the estimated velocity models for this simulation. As seen from figure 2, in this case, the neural network did not perform a good job. Although the network reconstructed well the velocity model at the training location, notice how it was not able to follow the horizontal velocity variations.

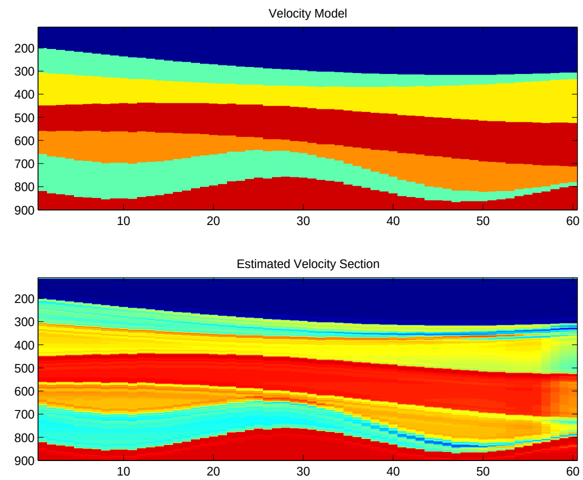

FIG. 1. Original and Estimated Structural Velocity Models.

It can be concluded from this result, and the one of simulation A, that the proposed technique is much more sensitive to stratigraphic variations, and much more robust to structural variations.

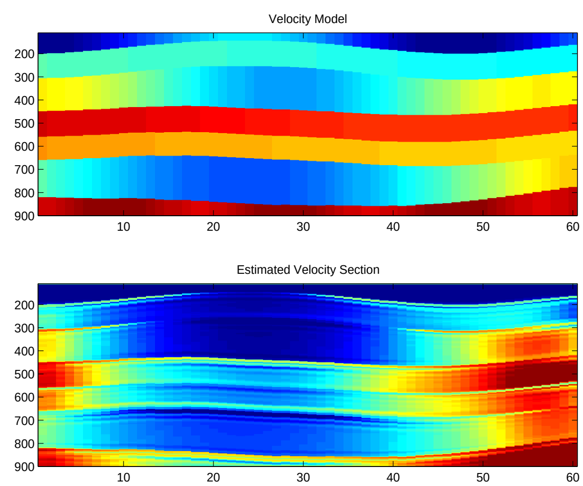

FIG. 2. Original and Estimated Stratigraphic Velocity Models.

‡Notice that since the vertical extension of the models is in time units, the layers of the stratigraphic model do not look flat in figure 2.

Finally, in simulation C, the stratigraphic model was used again. However, in this case, the neural network was simultaneously trained at positions 1 and 30 in the horizontal direction. Figure 3 shows the estimated velocity model for this simulation. In this case, as seen from figure 3, the neural network performed a better job than in simulation B.

It is evident that the incorporation of position 30 into the training process provided the network with more information about the spatial distribution of velocities. Then, it can be concluded that the number of training locations (well log data) is critical for the success of the method. The best the available well data represents the geology, the best the performance of the algorithm.

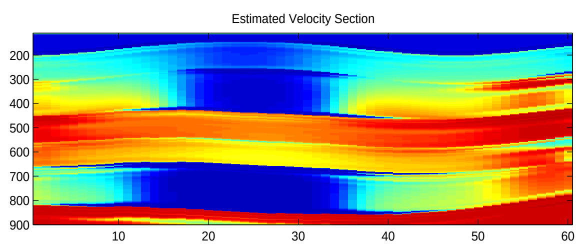

FIG. 3. Estimated Stratigraphic Velocity Model when Using Two Training Locations.

Field Data Examples

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 in eastern Venezuela. In the particular example presented here, it is intended to estimate spontaneous potential (SP) logs.

Spontaneous Potential logs, as well as Gamma Ray logs, are typically used as a lithological indicators since them allow to identify sand bodies in a direct way. For this reason, the generation of an estimated volume of SP in the field under consideration can be of great importance because it could reveal valuable information about the continuity of the sand bodies, which plays a critical role for defining the field recovery strategies.

Figure 4 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 $3.77\,Km$ by $1.52\,Km$, going from 100 to 350 in the in-line direction and from 250 to 350 in the cross-line direction. The time interval considered ranges from $1600\,ms$ to $1700\,ms$.

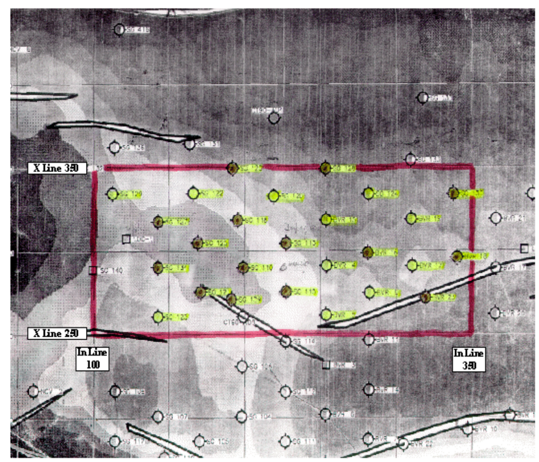

FIG. 4. Region Under Consideration and Well Locations.

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. Again, the back propagation algorithm was used for training the neural network.

Ten attributes were used in this experiment, they 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.

[§]Since petrophysical property measurements were not available in the field, the technique is going to be demonstrated with well log data.

ESTIMATED IN-LINE SECTION EXAMPLES Once the network was trained, it was used to estimate the whole volume of spontaneous potential. Figures 5 and 7 present two in-line sections of the estimated SP volume, at in-line coordinates 283 and 143 respectively. In these figures, the SP's smaller values, which indicate sand content, are represented in dark blue; and the SP's larger values, which indicate absence of sand, are represented in red.

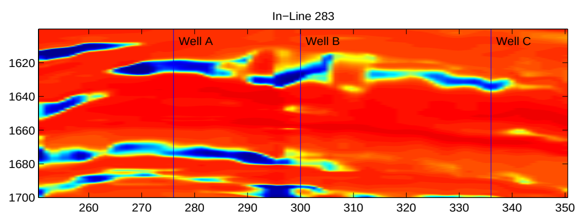

FIG. 5. Estimated Spontaneous Potential Section at In-Line 283.

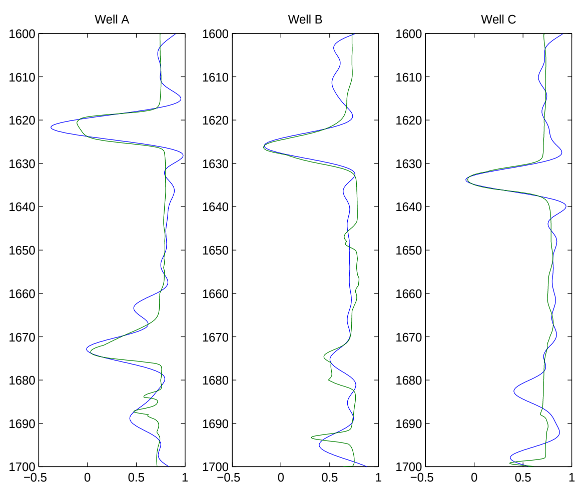

FIG. 6. Actual and Estimated SP Values at Well Locations A, B and C.

Notice from figure 5 that three wells (A, B and C) are located along the in-line section 283. Figure 6 shows the low-pass filtered versions of the actual SP curves (blue) and the estimated SP curves (green) at these three well locations. It can be seen from the figure how the estimated curves adjust to the actual curves. Notice, however, that the sand at 1680 ms in well C was lost[**].

The correlation coefficients obtained for the actual and estimated SP curves at wells A, B and C, were 0.93, 0.87 and 0.86, respectively.

Figure 7 presents the estimated SP section at in-line 143. Notice from the figure that other three wells (D, E and F) are located along this in-line section. Figure 8 shows the low-pass filtered version of the actual SP (blue) and the estimated SP (green) at these three well locations. Again, it can be seen from the figure how the estimated curves adjust the actual ones.

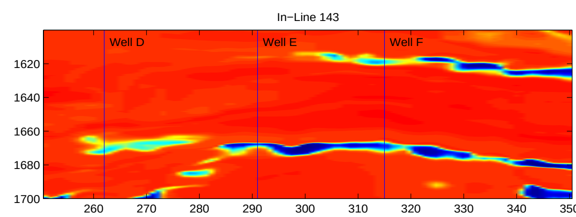

FIG. 7. Estimated Spontaneous Potential Section at In-Line 143.

In this case, as can be seen from figure 8, there are two sand bodies that were lost, the one at 1690 ms in well F and the one at 1620 ms in well D. The correlation coefficients obtained for the actual and estimated SP curves at wells D, E and F, were 0.85, 0.69 and 0.75, respectively.

ESTIMATED TIME SLICE EXAMPLES In this section, four time slice sections of the estimated SP volume at the time instants 1612.5 ms, 1615.0 ms, 1617.5 ms and 1620.0 ms are presented. This time slices, which are shown in figure 9, correspond to some of the sand bodies located between 1610 ms and 1630 ms. Some sections of these sand bodies can be appreciated in figures 5 and 7.

[**] This can be due to two different reasons, either the neural network training was not appropriately completed or, simply, the seismic data does not respond to that specific sand body.

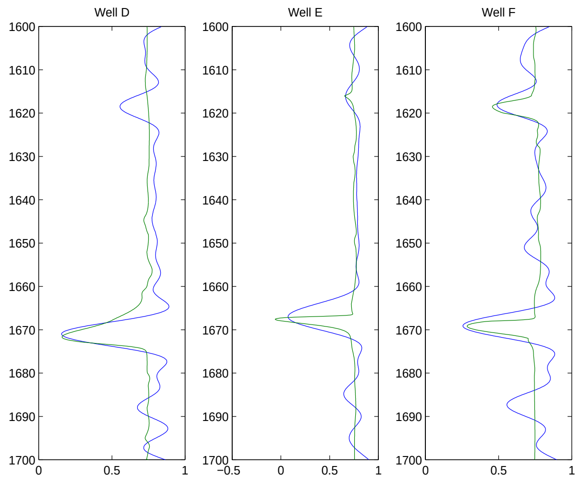

FIG. 8. Actual and Estimated SP Values at Well Locations D, E and F.

Conclusions

As illustrated in the previous two sections, the proposed methodology provides a good approach for estimating petrophysical properties and/or well log data from seismic attributes. Different from the conventional linear regression techniques, this method is able to infer the non-linear relationships existent between rock properties and seismic data.

A great advantage of this technique is the possibility of incorporate the spatial and temporal dimensions into the procedure. In this manner, the neural network is capable of learning spatial variations of the relationships between the data sets.

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

- The seismic data to be used must have been processed by preserving, as much as possible, its true amplitudes in order to preserve all the existent relationships between the desired properties and the seismic response.
- It is desirable for the petrophysical or well log data to be used to be contemporaneous with the seismic data to guaranty that both data sets are actually representing the same geology.

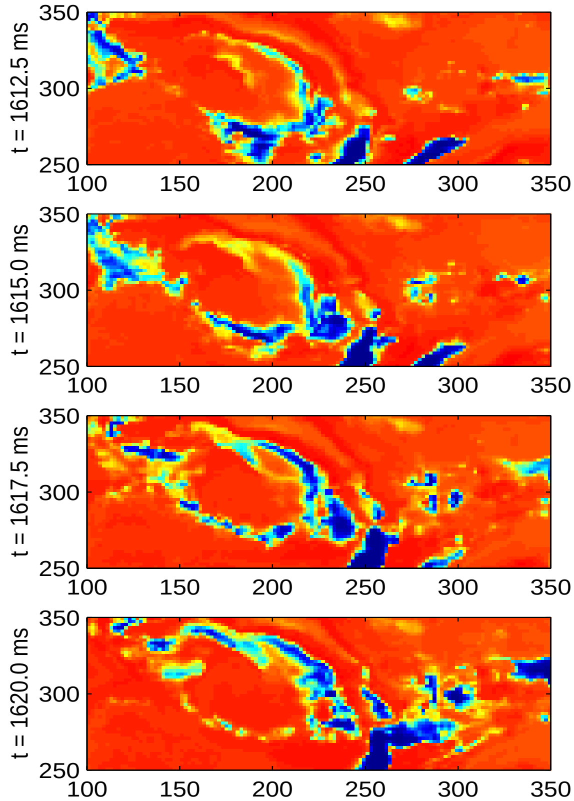

FIG. 9. Time Slices of the Estimated SP Volume.

- The depth to time conversion of well data is a very critical step of the procedure. For this reason, accurate T-Z curves are required.
- The quality of the resulting estimation will depend on how good, from a statistical point of view, the available well data represents the associated geology. In this way, the number of wells required will vary according to the complexity of the geology.
- As was verified with the synthetic simulations, the proposed technique is more sensible to stratigraphic variations and more robust to structural variations.
- The resolution of the resulting estimates are limited by the seismic data; i.e. the resolution of the estimated properties will depend on the frequency content of the processed seismic wavefield.

- The proposed technique is more appropriate for production than exploration geophysics since it requires representative well information. It actually performs a better job when interpolating than when extrapolating.

References

Brown, A. 1996, Seismic Attributes and Their Classification, *The Leading Edge*, Interpreter's Corner, October, pp 1090.

Chen, Q.; Sidney, S. 1997, Seismic Attribute Technology for Reservoir Forecasting and Monitoring, *WWW.EDGE-ONLINE.ORG*

Enachescu, M. 1993, Amplitude Interpretation of 3D Reflection Data, *The Leading Edge*, June, pp 678-685.

Haykin, S. 1994, *Neural Networks: A Comprehensive Foundation*, Macmillan, Toronto.

Hinton, G. 1989, Connectionist Learning Procedures, *Artificial Intelligence*, v 40, pp 185-234.

Oppenheim, A.; Schafer, R. 1989, *Discrete-Time Signal Processing*, Prentice Hall, Toronto.

Taner, M. 1976, *Extraction and Interpretation of the Complex Seismic Trace*, 46th Annual Metting SEG, Houston.

Todorov, T.; Hampson, D.; Russell, B. 1997, Sonic Log Predictions Using Seismic Attributes, *CREWES Research Report*, Volume 9, Calgary.

Todorov, T.; Stewart, R.; Hampson, D. 1998, Porosity Predictions Using Attributes from 3C-3D Seismic Data, *CREWES Research Report*, Volume 10, Calgary.