From 3D seismic attributes to pseudo-well-log volumes using neural networks: Practical considerations

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In recent years, neural-network-based methods for estimating pseudo-well-logs from existing well logs and 3D seismic data have been gaining popularity. Their main advantage over most traditional estimation methods is their ability to extract nonlinear relationships between the seismic data and the sparse set of well logs we want to interpolate. However, the process to go from seismic data and existing well logs to a dense 3D cube of pseudo-well-logs is not simple. The success of the estimation depends on the success of many critical subprocesses and choices that are not trivial and, as far as we know, have not been well documented in the literature.

In this paper, the steps we recommend for the estimation of pseudo logs from 3D seismic data are described. These steps are: selection of study area, preprocessing of well log and seismic data sets, neural network training, and generation of the pseudo-well-log volume. We explain in detail our usual practices related to the solution of key issues such as data aliasing, seismic resolution versus well-log resolution, selection of optimal neural network parameters, stationarity, and confidence intervals of the estimates. Finally, we show a field data example from eastern Venezuela, where a volume of spontaneous potential (SP) and its corresponding confidence intervals from 3D seismic attributes and 25 SP logs are estimated with this workflow.

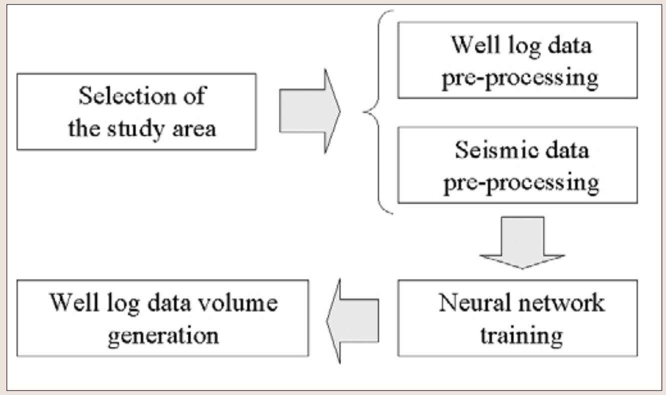

Figure 1. Steps of the methodology.

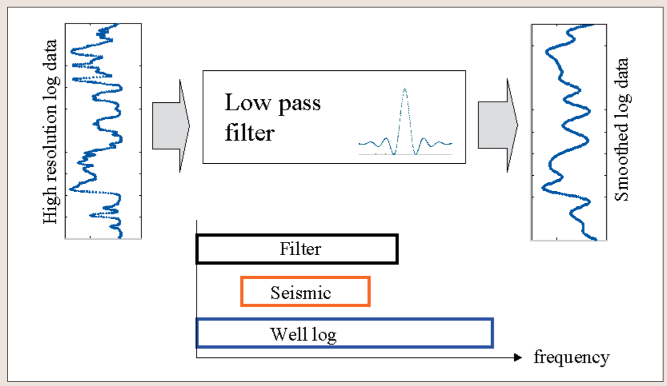

Figure 2. Smoothing well-log data resampled in time.

Pseudo-well-log estimation methodology. The methodology to go from seismic data to pseudo-well-logs consists of five steps (Figure 1):

1) Selection of the study area. To be able to use the methodology reliably, the data set should consist, at least, of:

- A seismic volume, processed preserving true relative amplitudes to avoid distorting existent relationships, if any, between the well logs and the seismic response.
- Accurate T-Z curves to perform depth-to-time conversion of well logs, which is a critical step of the procedure.
- Enough well-log data to provide a good statistical representation of the spatial variations of the study area.

Both well-log data and seismic data must be contemporaneous to guarantee that they represent the same in-situ conditions in the reservoir. The reliability of the final pseudo-logs will depend on whether the data set satisfies all conditions described above.

2) Well-log data preprocessing. In this step all well logs are converted from depth to time and the results are both resampled and smoothed. The first procedure is easily performed by using a T-Z curve and spline interpolators. Ideally, we should have a T-Z curve at each well of the given data set. In practice, however, this is not always possible and regional T-Z curves or T-Z curves from neighboring well curves have to be used.

Depth-to-time conversion yields well logs referred to time, but their samples are not uniformly spaced and do not necessarily coincide with the sample times of the seismic data. This means we must resample the well-log data. Because well-log sample intervals are much smaller than seismic sample intervals, many log samples will fall between two consecutive seismic samples after depth-to-time conversion. For this reason, a simple interpolation of the well-log information at the sample times of the seismic data can produce well-log estimates affected by aliasing. There are two options to overcome this problem:

- Low-pass filter the log data to limit their spectral content to that of the seismic data so that aliasing is avoided when downsampling log data to the seismic resolution.
- Resample the well-log data at uniform time intervals preserving its resolution and upsample the seismic data in order to match log sample times.

We prefer the second alternative because it increases the seismic data sampling frequency. This choice increases the size of the training data set and allows us to possibly broaden the bandwidth and thus increase the resolution of the resulting pseudo-logs.

Although nonlinear estimation methods may be able to increase resolution in some cases, we should not expect to obtain a transformation that goes all the way from seismic resolution up to well-log resolution because the spectral content of log data is much broader than the spectral bandwidth of the seismic data. This fact leads us to the third procedure, smoothing the resampled well-log data.

As Figure 2 shows, well-log data are smoothed by using a low-pass filter whose cutoff frequency is a little above the highest seismic frequency. How far from the seismic reso-

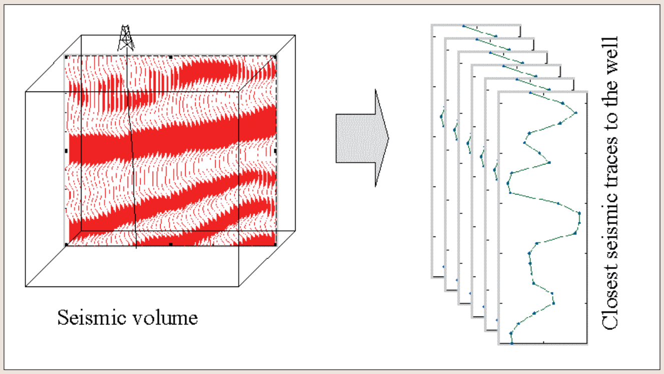

Figure 3. Extraction of seismic data around each well location

lution limit we can go is still a question to be answered. Trying to go too far above will severely affect the convergence during the training stage of the neural network.

3) Seismic data preprocessing. This consists of extracting from the 3D seismic cube the traces closest to each well, plus upsampling and averaging of such data. The extraction of the closest traces works well when we are dealing with vertical wells but may fail when wells are either deviated or horizontal. In these cases, pseudo seismic traces must be constructed along the well trajectories (Figure 3).

Once the traces have been extracted from the seismic volume, each trace is upsampled to generate a seismic sample at each time value at which a well-log sample exists. Upsampling can be easily achieved by using conventional interpolation filters or spline interpolation. This procedure increases the sampling frequency of the seismic data but it does not increase the seismic resolution.

Then, the information provided by the seismic traces at each well can be used to train the neural network.

4) Neural network training. The neural network architecture we use is the well known multilayer perceptron, which can be trained by using the popular back-propagation algorithm (Haykin, 1994). In the standard training strategy, two data sets must be created from the available data, a training set and a test set. The training set is the one used to actually train the neural network; the test set is used to provide a stopping criterion. Each element of these sets is composed of a well-log sample and its related seismic attribute samples.

At this point, to estimate a sample of each pseudo-well-log we can:

- Use all seismic attribute values from neighboring traces so that a spatial convolution operator is implemented.
- Use only the attribute value of the average trace of traces around the selected location.
- Use all seismic attribute values from a time window around the well-log sample location so that a time convolution operator is implemented. Instantaneous seismic attributes are the most suitable for this approach.
- Use only the seismic attribute value related to the same well-log sample location. Interval seismic attributes are the most suitable for this approach.

In theory, the combination of the first and third approaches should produce the most accurate estimates, because a cube of attribute samples is used to estimate each pseudo-log sample. However, to simplify and speed up the training process, we choose the combination of the second and fourth alternatives because it requires fewer input nodes for the neural network.

Convergence of the weight matrix during the training process and the resulting performance of the neural network estimation mostly depend on factors such as number of layers and neurons, type of activation function, and both data quality and size. However, the proper selection of algorithmic elements such as data normalization, output layer linearization, and both training and test sets selection can also improve the performance of the estimation.

5) Pseudo-well-log data volume generation. Once the neural network has been successfully trained it can be used to estimate a pseudo-well-log volume from the seismic volume. Notice that the same upsampling and averaging processes, applied in step 3 to the traces used to train the network, must be applied to the whole seismic volume prior to attribute computation.

Other important issues concerning attribute set selection and neural network parameter determination will be discussed in detail in the following section.

Parameter selection and confidence intervals. The solution to the problems of selecting the proper attributes and neural network parameters is more an art than a systematic procedure.

Let's start with the problem of attribute selection: Which attributes are the most adequate for the type of log we want to interpolate? How many attributes should we use? Traditional methods such as principal component analysis can help answer these questions, but they do not guarantee to produce the best set of attributes when using a nonlinear estimation technique. Although exhaustive search, or other techniques, such as stepwise regression (Hampson et al., 2001) can be used, more research is still required in this area.

We consider the time and space coordinates of each sample as crucial additional attributes. These attributes can help the neural network learn the spatial variations of the nonlinear relationships between the seismic data and well logs. Nonstationarity can be characterized by including these attributes. In particular, the time attribute (sample number) plays a very important role in helping the neural network follow the low frequency trends of the well-log properties. Similarly, in-line and cross-line coordinates are very useful to follow the lateral variations of the well log response. However, in areas with strong lateral variations, we should be careful when using these attributes if we don't have enough well control.

The problem of neural network parameter selection is also difficult. We must determine the amount of hidden layers and the amount of neurons at each hidden layer. In practice, we have found that two hidden layers offer the most appropriate tradeoff between training feasibility and network performance in the estimation problem. However, the problem of determining the total amount of neurons for each hidden layer is also difficult.

Both problems, attribute selection and neural network parameter determination, would be ideally approached as an optimization problem in which the total cross-validation error is minimized (the cross-validation error is the error resulting from estimating a well log that was intentionally excluded from the training procedure, and the total cross-validation error is the addition of the cross-validation errors computed for all the available well logs). However, in practice, this procedure can be extremely time consuming and difficult, so that attribute selection and neural network parameter determination becomes more an art than a standard procedure.

Once the best set of attributes has been found and the optimal neural network configuration has been determined,

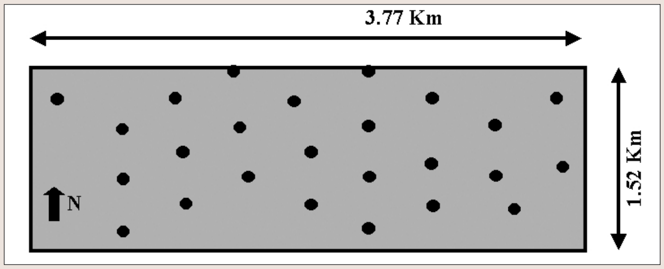

Figure 4. Region under consideration and locations of wells used to train the neural network.

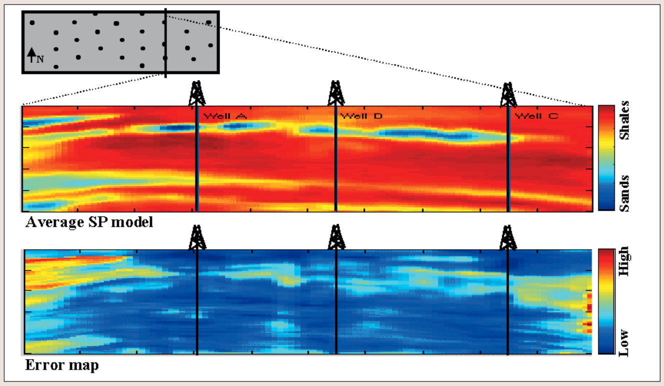

Figure 5. Cross-section of the average pseudo-SP volume and its estimated errors.

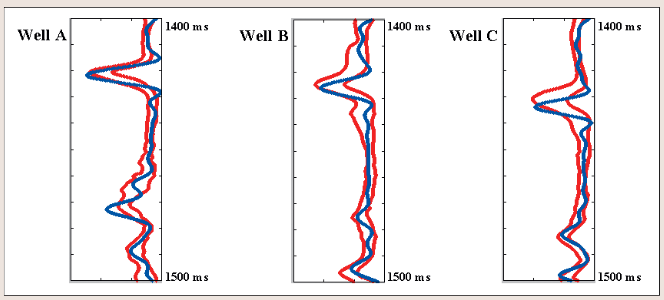

Figure 6. Actual SP curves (blue) and confidence intervals (between red curves) at three different wells.

the network can be trained to perform the subsequent pseudo-well-log volume estimation. However, different constructions of the training and test data sets yield different pseudo-log volumes. This means each training exercise can be considered as a particular realization of a statistical simulation, which will basically depend on how the available data are separated into training and test sets. In this way, multiple training exercises will allow us to perform a Monte Carlo simulation, from which a distribution of pseudo-well-log volumes can be generated. From this distribution, we can obtain the most probable pseudo-log volume along with its confidence interval, as shown by Banchs and Michelena (2000).

Field data example. To illustrate the methodology described above, we estimate a pseudo SP-log volume from 3D seismic attributes in a field from eastern Venezuela. In this field, SP logs have proved good lithological indicators and, therefore, we expect a volume of pseudo SP logs can reveal valuable information about the continuity of sand bodies. This information is critical to determine the proper recovery strategies for the reservoir.

Figure 4 illustrates the region under consideration for our test and all wells used for training the neural-network-based estimator. The total extension of the study area is 3.77 × 1.52 km, and the time interval was 1400-1500 ms.

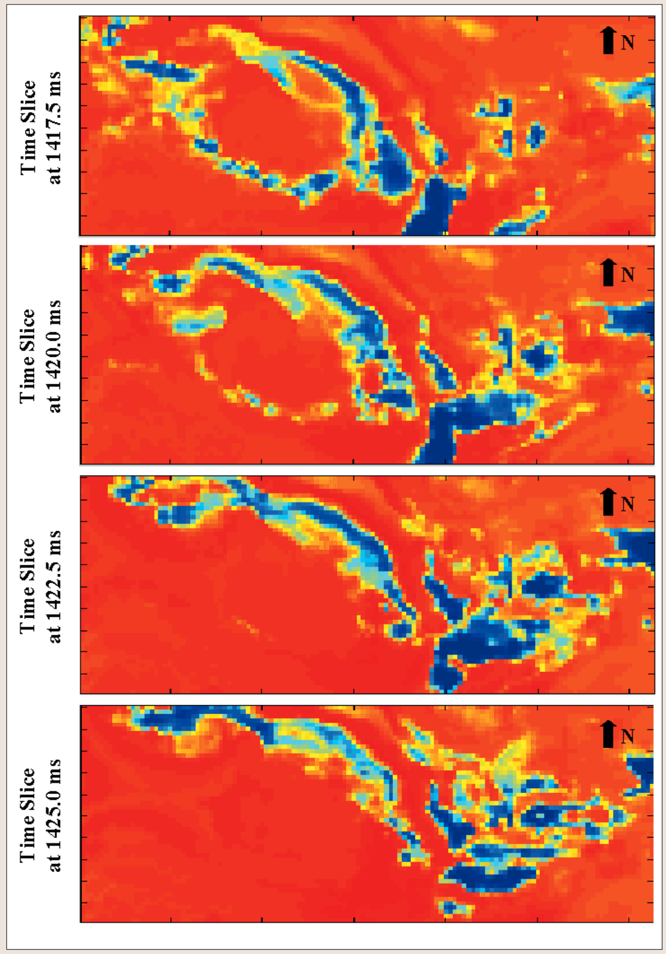

Figure 7. Time slices of one pseudo SP log volume realization. Sands are blue and shales red.

We used 25 SP logs to train the neural network, which consisted of a four-layer perceptron with 10, 12, 12, and 1 neurons in each layer, respectively. Ten seismic attributes were used in this exercise: sample number, in-line coordinate, cross-line coordinate, time integral of the amplitude, time integral of the absolute amplitude, instantaneous phase, derivative, second derivative, average frequency, and average amplitude.

The number of neurons in the hidden layers and the seismic attributes were empirically selected after some experimentation following the criteria described previously. Once we determined the best set of seismic attributes and the neural network parameters, we performed 70 independent simulations (with different training and test data sets). From these simulations, we extracted the most probable pseudo-SP-log volume and its associated confidence interval.

Figure 5 shows a cross-section of the resulting pseudo-SP-log volume along with its estimated error. Notice the presence of sand lenses (blue) which are consistent with the sedimentological model of the reservoir. Estimation errors between wells are lower than errors in the borders of the study area which means the methodology works best when interpolating rather than extrapolating information.

The correlation coefficients between actual and estimated SP curves at wells A, B, and C are 0.92, 0.83, and 0.72, respectively. Figure 6 shows the actual SP curves (blue) along with the estimated confidence intervals.

The confidence curves in Figure 6 were computed by adding and subtracting the estimated error to the average pseudo-SP values at each well. Notice how the actual SP curves tend to remain bounded by the estimated confidence curves.

Figure 7 shows four time slices corresponding to one of the 70 simulations performed to estimate different pseudo-SP-log volumes. Notice how, as time increases, a structure is evidenced on the left of the sections. This result confirms the existence of a dome in the reservoir model and contributes to map accurately the location of producing sands (blue).

Final remarks. Dense 3D volumes of pseudo-well-logs can be estimated from 3D seismic data and sparse real logs using neural networks as the estimation engine. The use of neural networks allows inferring the nonlinear relationships that may exist between the given well logs and the seismic data. This process, however, is not straightforward and the accuracy of the estimates depends on many factors such as quality of seismic and well-log data, processes applied to these data, frequency content and resolution, heterogeneities of the reservoir, and both seismic attributes and neural network parameters selected for the estimation.

In this paper, we have explained in detail what we consider, from our experience, good practices to handle the whole process, from data preprocessing to estimation of confidence intervals, such that the final pseudo logs are good estimates of all given logs. However, even though the methodology offers important advantages such as the ability to incorporate spatial and temporal variations in the relationships between seismic data and log data, it still requires much more research and practical tests to be able to determine systematically the best set of attributes used for the estimation, to determine the best combination of neural network parameters that optimize its performance, to obtain faster confidence intervals, and to determine how far beyond the seismic resolution we can expect to go with this kind of nonlinear estimators.

Suggested reading. "Well-log estimates and confidence intervals by using artificial neural networks" by Banchs and Michelena (SEG 2000 *Expanded Abstracts*). "Use of multiattribute transforms to predict log properties from seismic data" by Hampson et al. (GEOPHYSICS, 2001). *Neural Networks: A Comprehensive Foundation* by Haykin (Macmillan, 1994). "Seismic-controlled nonlinear extrapolation of well parameters using neural networks" by Liu and Liu (GEOPHYSICS, 1998). "Seismic guided estimation of log properties" by Schultz et al. (*TLE*, 1994). "Seismic attributes, their use in petrophysical classification" by Taner et al. (SEG 2001 *Expanded Abstracts*). "Seismic reservoir characterization of a mid-continent fluvial system using rock physics, poststack seismic attributes and neural networks: A case history" by Walls et al. (SEG 2000 *Expanded Abstracts*). TLE

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