Prediction of lateral variations in reservoir properties throughout an interpreted seismic horizon using an artificial neural network

Darío Sergio Cersósimo[1], Claudia L. Ravazzoli[2], and Ramón García Martínez[3]

Abstract

Successful use of an artificial neural network is shown to predict lateral variations of seismic velocity, density, thickness, and gamma rays associated with sand dune reservoirs identified on a previously interpreted seismic horizon. The work is presented in two main sections. Section one is a feasibility analysis based on synthetic data. A known geologic model is used, performed by pseudowells, in which lateral variations in seismic velocity, density, and gamma ray values are related to the dunes. The synthetic seismic model and the attributes derived are used as training input in the neural network. Section two is a real case example where the methodology is applied to a real seismic data set. Results indicate that using a set of data and attributes restricted to a time interval corresponding to a previously interpreted seismic horizon is more efficient than using a whole data cube, involving a very large volume of data.

Introduction

Neural networks as a particular case of intelligent systems have given promising results in many fields, such as modeling, time series analysis, and pattern recognition, among others. In the field of geophysics, these methods have gained popularity during the last decades to solve a variety of problems, as explained by van der Baan and Jutten (2000) and Sandham and Leggett (2003). In particular, neural networks have proven to be useful in reservoir characterization, as shown in An and Moon (1993), Sandham and Leggett (2003), and Herrera et al. (2006).

In this work, a solution for the problem of horizontal prediction of properties was carried out through pseudowells and seismic horizons previously interpreted over a 3D seismic cube. The main premise of this paper lies in the fact that the process of the seismic attributes is performed through the interpreted horizon of a synthetic model. This synthetic seismic model was created by the convolutional model between the reflection coefficients obtained from the velocities and densities and a given seismic wavelet.

For both the synthetic and the real case, the artificial neural network (ANN) was used for the geophysical characterization of sand dune fields. As pointed out by Morse (1994) and Krittian and Naides (2006), sand dune deposits are usually clean and well-sorted and therefore constitute excellent hydrocarbon reservoirs and carrier beds. Well data in these formations provide detailed vertical information and may indicate lateral trends, but cannot specify intrawell information. Therefore, the determination of lateral variations in different geophysical properties combining reflection seismic horizons, related attributes, and well data is a problem of great interest in hydrocarbon exploration and characterization.

Feasibility analysis based on synthetic data

In this case, we propose a simple synthetic geologic model (Cersósimo et al., 2006) consisting of three horizontal layers, in which the middle layer is thin and has lateral variations in seismic velocity, density, and natural gamma ray (GR). This heterogeneous layer contains the dunes and interdune zones.

The attributes to be used as input in the neural network were calculated within a window containing the seismic event associated with the composite reflection from the thin layer.

In general terms, the synthetic data were obtained using the following procedure:

- creation of a seismic velocity cube from a particular velocity model, including lateral variations (In this case, the variations are related to the presence of a dunes model with a thickness of 10 m.)
- derivation of a density cube from velocities
- computation of an acoustic impedance cube
- definition of a zero-phase, 30 Hz Ricker wavelet
- creation of a synthetic seismic amplitude cube, using the information from previous steps
- identification and interpretation of the seismic reflector and calculation of the seismic attributes to be used in the neural network
- creation of a training matrix, with the attributes chosen and known GR values at some discrete locations
- application of the training matrix to the entire seismic cube to obtain the desired output

The initial velocity cube was designed with geologic criteria, considering three layers. The upper layer of the model, from 2000 m to 3000 m deep, is a shale with a velocity of 3200 m/s. The second layer is a thin bed of marls with intercalated clean sandstone dunes, located at depths from 3000 m to 3010 m with a base velocity of 3100 m/s (corresponding to the marl interdune zones). The third layer, from 3010 m to 4000 m has a constant velocity of 3300 m/s. A vertical slice of the velocity cube is shown in Figure 1, in which the assumed GR values for each lithology also are included. In Figure 2, we plot a horizontal slice of the synthetic velocity cube generated; the yellow cells represent the dunes. Note that each yellow and red cell will store the velocity and the density, and each green cell will store the velocity, density, and the property to be predicted. The green cells in Figure 2 will be the input for the training phase.

Once the compressional velocity cube was created, the density was obtained using the Gardner equation (Gardner et al., 1974).

[1]GALP Energía.
[2]CONICET and Universidad Nacional de La Plata, Argentina.
[3]Universidad Nacional de Lanús, Argentina.

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Then, using the density cube, the velocity cube, the geologic model, and the wavelet, the synthetic seismic cube was generated. The seismic traces were computed by means of the convolution of the reflection coefficients, given by the acoustic impedance contrasts of the model and the 30 Hz Ricker wavelet (Figure 3). Using the synthetic seismic cube, a horizon related to the layer of interest was interpreted (marked with a blue line), in which significant lateral amplitude variations associated with the dunes can be observed. This horizon represents the center of the target. A 30 ms time window centered about the interpreted horizon was used for the attribute calculations. This window width was selected based on the widths of the well logs and the seismic data.

Along this interpreted horizon, different attributes were defined and calculated, such as spatial coordinates (denoted X, Y), RMS amplitude, isochronous map values of an interpreted horizon, instantaneous phase, integrated RMS, trace length, quadrature, and others.

The ANN used in this work is a back propagation network, which is an algorithm for supervised learning. Basically, the algorithm is divided into two phases. A stimulus pattern is applied to the input of the network; this propagates from the first layer through the upper layers of the network to generate an output. The output signal is compared to the desired output, and an error signal for each of the outputs is calculated. The error outputs propagate backward from the output layer to all the neurons in the hidden layer that contribute directly to the output; however, neurons of the hidden layer receive only a fraction of the total error signal based on the relative contribution that each neuron has provided the original output.

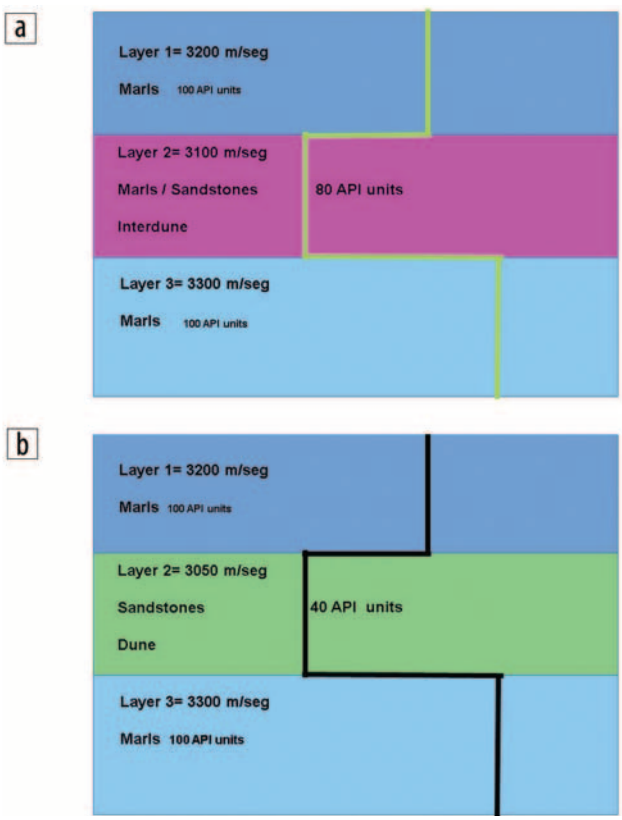

Figure 1. Vertical slice of the velocities of the model at (a) interdune zones and (b) dunes.

This process is repeated layer by layer, until all neurons in the network have received an error signal describing their relative contributions to the total error. The importance of this process is that, as the network is trained, the neurons in the intermediate layers organize themselves so that different neurons learn to recognize different features of the total input space. After training, when presented with an arbitrary input pattern that is incomplete or contains noise, the neurons in the network's hidden layer will respond with an active output if the new entry contains a pattern that resembles that characteristic that individual neurons have learned to recognize during the training session (Freeman and Skapura, 1991).

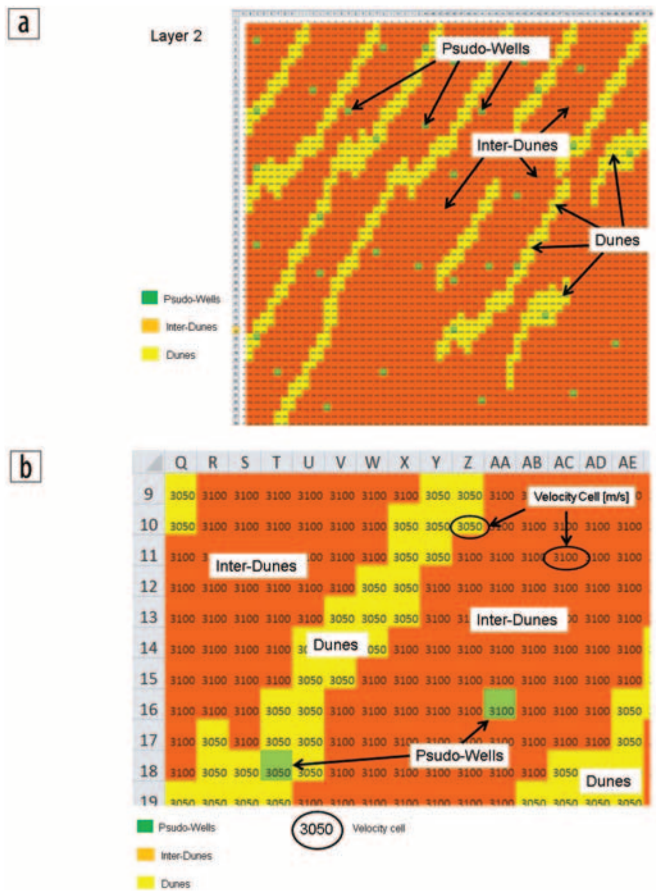

Figure 2. (a) Horizontal slice of the velocity model corresponding to Layer 2. (b) Enlargement of the small area selected in (a). The dunes are marked in yellow and the interdune zones in red. The green cells are the data used for training the ANN. The numbers denote the velocity for each cell in m/s.

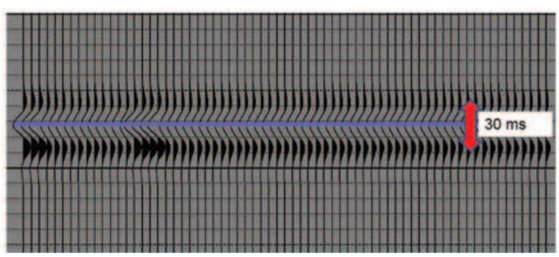

Figure 3. Detail of the synthetic seismic data window used for the calculation of the seismic attributes throughout the interpreted horizon.

In Figure 4, we illustrate the architecture of the ANN used for the present case, in which we specify the seven attributes used to generate the input, which were randomly selected. This network presented a single hidden layer and a single desired output, which, for this case, was the distribution of GR along the interpreted horizon.

Regarding the choice of input attributes, it should be pointed out that the ANN does not guarantee that the given solution is optimal and unique. In fact, it must be tested by different numbers of hidden neurons, activation functions, learning rules, etc., until a correct solution is obtained. This final solution has to be the most consistent with the geology of the area under study. Using this criterion, we trained the ANN with a random number of attributes and parameters. Thus, the seven attributes shown in Figure 4 were selected because they produced the most consistent results.

The GR training data were obtained from the pseudowell data of the area (the green cells in Figure 2), with values of 80 API units for marls/sandstones in the interdunes, 40 API units for sands in the dunes, and 100 API units for the upper and lower layers. The impact of the velocity variation in the amplitudes of any attribute can be observed, but with the values related to the attribute in question. That is, in many cases it is likely that attributes reveal the shape of the event to be characterized, but what is important is what the ANN scaling will provide as a final product.

In Figure 5, we plot the values obtained by the ANN for the GR distribution throughout the selected horizon. The close match between the spatial pattern of these results and the synthetic initial model (Figure 2) shows the good performance of the method to predict dune locations. However, the existence of some small, dispersed false dunes can be noted, which are mainly associated to the selected attribute training set. Using a different set of attributes would result in another pattern distribution, as expected.

Real case

In the previous section, we solved the forward problem to generate a set of synthetic data, and then we applied the proposed ANN methodology to recover the original model. Here, application of the described method is demonstrated with real data from a sand dune reservoir in Argentina. In this case, the control of the results is done through the analysis of spectral decomposition of seismic data, well-data information, and basic seismic interpretations done in the area. In this way, this comparison allowed us to conclude that the proposed methodology works very well.

As in the previous case, the neural network used was a back propagation network. For this particular case, seven randomly chosen attributes were used to obtain a desired output of four curves:

- acoustic impedance
- gamma ray
- density
- thickness

The architecture of this neural network used with real data is shown in Figure 6. These attributes were calculated along a horizon around the area of interest and within a search window of 8 ms. The time window was chosen according to the thickness in time over the well logs associated with the dune reservoir. Figure 7 shows the spectral decomposition process on the real seismic data, corresponding to 32 Hz, in which it is possible to see the geologic trend in the area of interest. The dunes are associated to the elongated white amplitude zones along the east-west direction.

ANN training was performed with known data from eight wells with real log data, which are not marked in the figures due to confidentiality reasons. The area of analysis is about 50 km^2,

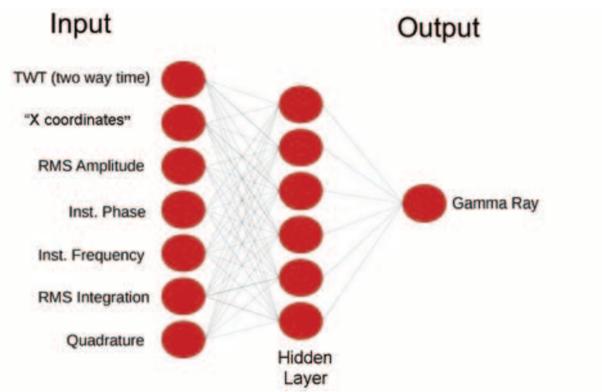

Figure 4. Architecture of the applied neural network indicating some of the attributes used for the synthetic data example.

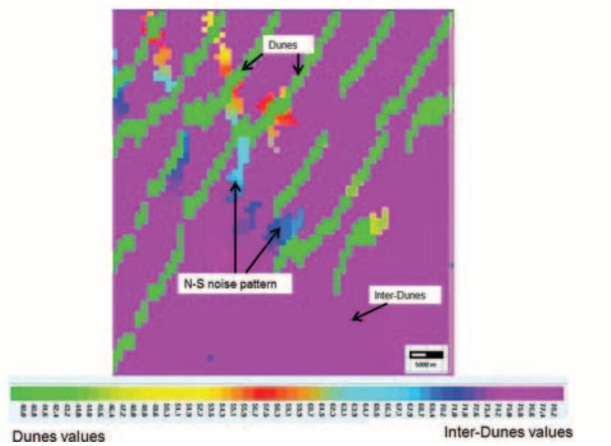

Figure 5. Final product of the neural network showing the horizontal distribution of GR. Note the very good correlation between the GR results and the synthetic model in Figure 2.

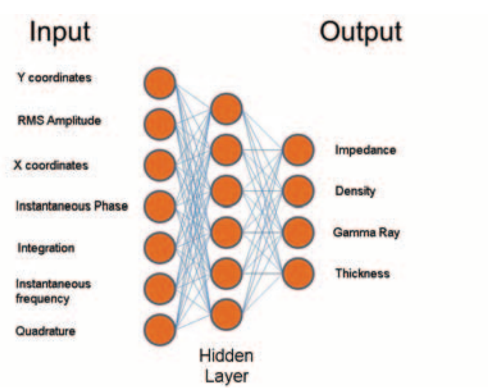

Figure 6. Back propagation architecture for the real data.

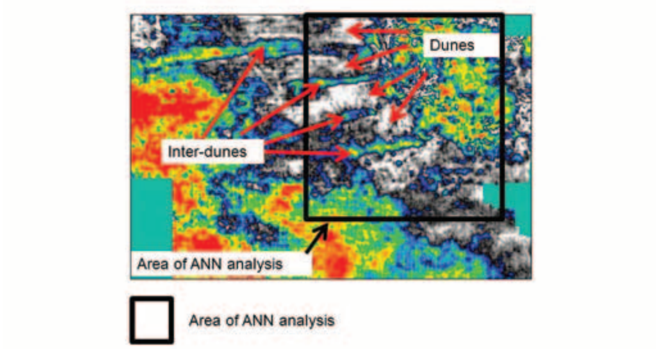

Figure 7. Spectral decomposition applied to the real seismic data. The dunes are represented by the white amplitude response. The picture corresponds to a horizontal slice at 32 Hz.

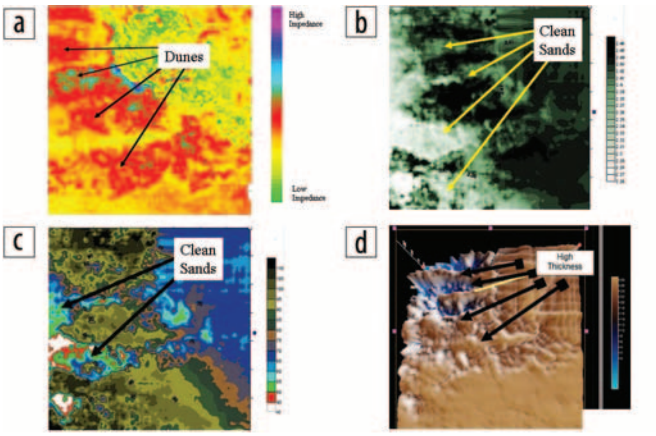

Figure 8. Results obtained using the ANN on real data: (a) P-impedance, (b) density, (c) gamma ray, and (d) tridimensional image of dune thicknesses.

the stacking bin size is 25 by 25 m, and the vertical data were sampled at 2 ms. The horizontal distances between wells are about 500 and 1000 m.

The logs used are gamma ray, thickness, velocity (calculated from sonic logs), and density. The data to train the ANN from the well data are coming from the average value in the time window of the log associated with the reservoir. The amplitude of the attributes to be used in the training process were extracted from the average of the four seismic attribute traces nearest the well and from the seismic time windows also related to the reservoir.

Using an average of the log information around the reservoir zone, and an average of the attributes around of the seismic zone associated with the reservoir, gave us the opportunity to attenuate the frequency differences between the high-frequency log and the low frequency of the seismic data. With this in mind, we are associating each amplitude of the attribute with each log property.

Results

Figure 8a shows the P-impedance calculated by the ANN, in which the main trend of the dunes can be observed. The dunes are associated with the medium impedance represented by the yellow shapes.

In Figure 8b, we show that the neural network could discriminate, with very good detail, the density of the dunes. Observe that the lower densities in this picture can be used to delineate the sand dunes.

Figure 8c shows the pseudo GR results from the ANN. The low GR values are associated with the clean sands in this area, and the higher values are associated with shale bodies. The previous analysis was verified with the wells in the area. In this case, the GR response indicated that the green, red, and white areas represent clean sand bodies with good petrophysical conditions for hydrocarbon entrapment.

Finally, in Figure 8d we display the predicted thicknesses, in which we observe that the spatial variations are consistent with the other outputs obtained by the ANN. As in previous figures, the dunes lie in the east-west direction, having thicknesses below 28 m.

At the northeast of each figure, grid-shaped variations can be observed; these are caused by some seismic noise and footprint in the area. To the south, it is possible to see a flat event; this is a possible change in lithology and thickness.

Conclusions

In this work, we showed the feasibility of using a back propagation ANN to detect lateral variations in seismic attributes and parameters associated with sand dune reservoirs located on a previously interpreted seismic horizon.

From the present analysis, we conclude that the ANN gave excellent results for density, GR, and thicknesses, showing areas with good petrophysical conditions. These areas were corroborated with well data. For synthetic data, the method was successful to discriminate the lateral variations, which made it possible to delineate the dunes, even for thicknesses well below the vertical seismic resolution. Although the number of well data for the training of the network is critical to the final results of these processes, it was observed that the geographic distribution of input data is fundamental to get a response consistent with the geologic model. It is highly recommended to perform a feasibility analysis, such as the one presented with synthetic data, before the application of these kind of procedures.

We remark that the described procedure is novel and, to our knowledge, has not been implemented in this way before. It allows us to combine dispersed well log information and different attributes taken within selected data windows associated with the seismic horizon of interest, instead of using the whole seismic cube. Our results with synthetic and real data allow us to suggest that the proposed ANN procedure may be a useful tool for reservoir characterization and delineation. TLE

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Corresponding author: sergio.cersosimo@galpenergia.com

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