4-D cross-equalization and offset equalization using a Neural Networks approach

Uri Zakhem , Anat Canning and Alex Litvin, Paradigm Geophysical, Israel*

2005 CSEG National Convention

Summary

A statistical approach to time-lapse cross-equalization, using a back-propagation Neural Network technique is presented. Analysis of the differences between two vintage datasets is done by training at a region away from the production zone. The same concept is used for offset equalization prior to AVO analysis. Synthetic tests and a real data example are presented, demonstrating the concept.

Introduction

The differences between two vintage datasets need to be minimized when cross equalizing time-lapse data. The objective is to map the variations due to production, while minimizing those resulting from different acquisition and processing procedures. We distinguish between two types of variations between the datasets, local and global. Local variations could have been caused, for example, by differences in the acquisition grids and parameters, or by variations in the velocity models used to process the two datasets. Global refers to the variations that exist at any location. These, for example, can be due to differences in source and receiver signature or in processing.

Global variations between different vintage datasets are traditionally minimized using a combination of deterministic wavelet matching techniques and cross-correlations. In this paper we propose a statistical approach to cross-equalization. For this purpose we assume that the differences between the two datasets can be very complex, but they are global for the data. This means that overall the same differences can be detected at any location in the dataset except in the vicinity of the reservoir. Based on this assumption we analyze the difference between the two datasets at a region away from the production zone. We then find a single operator which maps one dataset to the other. Finally, we apply this operator to the whole input dataset and obtain two equalized datasets where the difference due to production can be easily mapped.

We use the Neural Networks approach to find this operator. It allows us to define a non-linear, multi-dimensional operator, which can handle complex mapping of one dataset to the other, and does not rely on any deterministic theory to explain the differences between the two datasets. The Neural Networks technique is ideal for finding the general rule from a set of specific examples, and therefore is very suitable for solving the cross-equalization problem.

We use the same approach for offset equalization. Offset equalization is often required for AVO analysis. Here variations from one offset to another (or variations between angle stacks) due to NMO stretch, phase rotations, amplitude scaling and other wavelet distortions, need to be minimized. In this case we select some key horizons, where we expect to have minimum AVO variations. We define a target offset (mostly one of the far offsets), and use the Neural Networks technique to find an operator which will map the data from one offset to the target offset, so that the differences are minimized. Note that in this case a different operator is defined for each offset (or angle stack). To preserve AVO, the average original AVO response of the input data can be mapped before the process, and restored at the end.

Method

The Neural Networks technique is a two-phase process. The first phase is a training phase where a generalized operator that maps the input training dataset to the desired output is derived. The training set is a representative subset of the seismic data. The second phase is an application phase where the operator is applied to the entire data.

The operator is defined using a multi-layer perceptron Neural Networks structure. We construct a convolution-like operation in which a single input-desired output pair is composed of *n* input samples, and is used to predict a single output sample. *n* corresponds to the typical wavelet length in the dataset. Figure 1 presents a general architecture of the network. In this network the weights w_i and biases (b) are defined at the hidden layers and at the output. Each neuron (x_i; black dot) calculates a weighted sum and adds a bias (b): $y = f\left(\sum_{i=0}^{m} x_i w_i + b\right)$, where *f* is an activation function and *y* is the output value. The weights, including the bias, are determined by training using a back propagation algorithm (Fausett, 1994, Calderon et al, 2000). A

combination of very fast simulated annealing and back propagation can be used.

Note that the training dataset is constructed using a running window of length n to define input-desired output pairs within each input trace. Adding various seismic attributes as additional input to the network enhances the cross-equalization procedure. We use two types of attributes. The first are complex trace attributes (Tanner) such as signal envelope, amplitude weighted instantaneous phase etc. The use of such attributes can enhance network flexibility and resolution power. The other type of attributes includes time or depth (which can be measured from a reference horizon) and the horizontal coordinates.

These allow us to define an operator that is time (or depth) varying as well as laterally varying. Note that these variations are usually long wavelength variations. Both types of input attributes are included in the network as additional input points for each training set.

For the training stage a small, high data quality region is used. We normally define a time window that follows a dominant horizon.

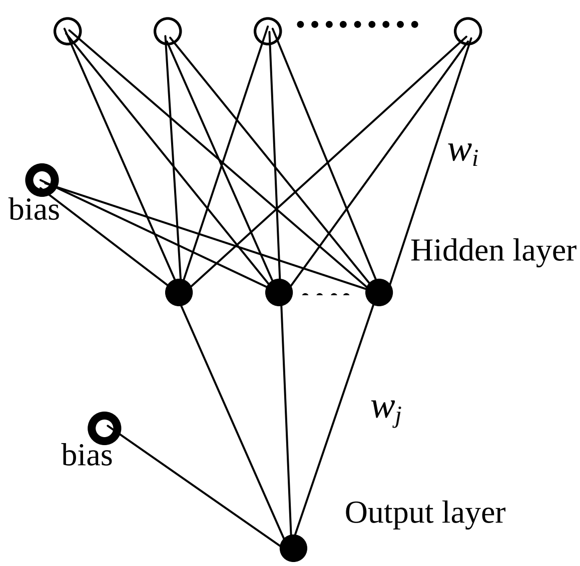

Figure 1: The Neural Network architecture.

Examples

Synthetic tests were designed to show the ability of the Neural Networks operator to:

- Handle complex wavelet differences
- Handle time shifts between the two datasets
- Separate between local changes and global changes
- Extract a global operator when training data contains interferences
- Handle differences, which are a function of time.

Figure 2 presents a synthetic example that was generated from real well logs within a complex structure. Two Normal Incidence reflectivity sections were generated using very different wavelets (different amplitude and phase spectrums). One section (a) was used as input to the Neural Networks cross-equalization program and the other was used as the desired output (b). The result of cross-equalization (c) shows an excellent match to the desired output. Training was performed on the window marked with a rectangle on (a).

Figure 3 presents a synthetic test that was designed to show that the operator derived using the Neural Networks procedure can be used to separate between local changes and global changes in the data. This dataset has three reflectors, the first two reflectors have an identical reflectivity response. The third reflector has amplitude, which is constant on the input data (a) and gradually increases to the east in the desired output data (b). The difference between desired output and actual output (c) shows that the procedure preserved local differences between datasets while minimizing the global ones.

The test presented in Figure 4 uses a dataset similar to the one used in Figure 2. In this case, the input was created as in Figure 2, and the desired output (b) was created with an amplitude decay due to geometrical spreading. This introduced a difference in amplitudes which is time (t) varying. To handle the time variations we used time as one of the attributes in the network. Comparing desired output (b) with actual output (c) demonstrates that this network construction can be used to find time dependent variations.

The application of the Neural Networks approach to offset equalization is demonstrated using a real dataset (Figure 5). Here we used the near angle stack (a) and the far angle stack (c) as the input and the desired output to the procedure. The objective was to transform the near angle stack to better match the far angle stacks, and thus achieve “offset” equalization. The dataset was acquired from an oil field with an AVO anomaly (marked on c). This anomaly created significant differences between the near and the far offset data in the vicinity of the reservoir. The objective of the procedure is to preserve the anomaly, while matching the character of the data. Consequently, the training was performed away from this reservoir zone. We used, as a training set, the data within a time window that followed the lower strong horizon (pink). The result, an equalized near angle stack, is presented in Figure 5b. It shows that the overall character of the output data matches that of the far angle stack (the desired output) in terms of wavelet shape and frequency content, and the AVO anomaly is still preserved.

Conclusions

Neural Networks technique can be used to define an operator for matching two datasets. Our experience shows that results can be improved when this procedure is applied after standard deterministic procedures. This way the Neural Networks technique is used to resolve the residual differences.

References

Calderon, M., 2000, Artificial Neural Networks for parameter estimation in Geophysics, Geophysical Prospecting, Vol. 48 p. 21-47.

Fausett, L., 1994, Fundamentals of neural networks, Prentice-Hall.

Taner, M.T., Adaptive deconvolution and cross equalization, www.rocksolidimages.com/pdf/adaptive_decon.pdf

Taner, M.T., Attributes revisited, www.rocksolidimages.com/pdf/attrib_revisited.pdf