Neural Networks Approach to Spectral Enhancement

Anat Canning, Dominique Moulière-Reiser, Yuval Weiss, Alex Malkin, Eitan Philip, Nimrod Grinberg, Anastasya Teitel, Margaret Reznikov and Vardit Yehezkel, Paradigm.*

Summary

We present an artificial intelligence approach for enhancing the frequency spectrum of seismic data. We used synthetic seismic data as a training dataset for constructing a neural networks operator that can solve the posed problem. We then applied this operator to real seismic data and obtained broader frequency spectrum.

Introduction

Artificial intelligence algorithms have received a lots of attention in recent years. In the context of seismic data processing and interpretation, the range of problems which can benefit from an artificial intelligence approach is very broad. In SEG 2003 (Zakhem et. al.) we presented a novel approach for achieving various seismic processing objectives using neural networks. At that time we discovered that with special adaptation of a back propagating neural Network to seismic data we can approach many problems that are normally solved using classic deterministic procedures. In that paper we presented several examples of using artificial intelligence for seismic data operations. We showed neural networks implementation for 4D cross-equalization of multi vintage data as well as offset equalization of prestack data. Neural networks are used here instead of classic deterministic procedures like wavelet estimation, deconvolution etc. The idea is that if you can provide a training dataset, i.e. input and desired output pairs, then you can construct a neutral networks operator which can perform the conversion from input to the desired output. The challenge is of course to produce an operator which is a generalization of the problem rather than specific to the specific training dataset. For example, in the classic approach if we want to equalize two vintage datasets from a 4-D survey we will design a "matching filter" in Fourier's domain to perform this procedure. One filter that will be applied to the entire dataset. We expect the neural networks system to work in a similar way, i.e. provide one filter that will be applied to all the traces in the dataset. In that sense this filter will "generalize" the problem. The difference between a filter designed via neural networks and a classic deterministic filter is that the neural networks filter is non-linear, multi-dimensional and can be quite complex. It can therefore handle the complexities in the data which we do not include in our deterministic models.

In this paper we present an implementation of our neural networks algorithm for broadening the frequency content of seismic data. Enhancing the frequency spectrum is a major challenge in seismic science for many years. This topic is quite controversial, but we do not intend to get into the discussion over the associated controversies. We are still in a research mode investigating the new world of possibilities based on this unorthodox formulation. We will show here our results and explain our approach.

The neural networks technique is a two-phase process. The first phase is a training phase where a set of examples for the procedure we want to perform are analyzed and a generalized operator mapping the input training set to the desired output set is derived. The second phase is the application phase where the operator is applied to the "input data" to obtain the "output data".

One of the main elements in the success of neural networks techniques is good posing of the problem we wish to solve. In our 2003 paper we tried to solve the 4-D cross-equalization problem. For that problem we used one vintage dataset as the "input data" and the other vintage dataset as the "desired output data", we derived a neural networks operator that transforms "input data" to the "desired output data". This operator was then applied to the "input data" to obtain the "output data" which is the equalized dataset. The trick was to perform the training outside the reservoir zone, where all the changes between the two datasets could be attributed to acquisition and processing differences (which were the effects we wanted to equalize) and not to the changes in production (the effects we wanted to preserve). The results we obtained were very encouraging.

Method

There are many similarities between the approach we took for 4-D cross-equalization and the approach we take here for spectral broadening. We used a similar operator construction designed specifically for seismic data and is described below. The main difference is that for spectral broadening we used synthetic training data, and applied the operator to the real data in order to obtain the frequency broadening. In other words, we designed the operator using synthetic examples. The synthetic examples were constructed so that the frequency spectrum of the synthetic "input data" (wavelet) mimics real input data – the one we want to broaden its frequency. The "desired output" for training was a synthetic dataset created with a wider frequency range. We then use the neural networks training process to define the frequency broadening operator and apply it to the real data.

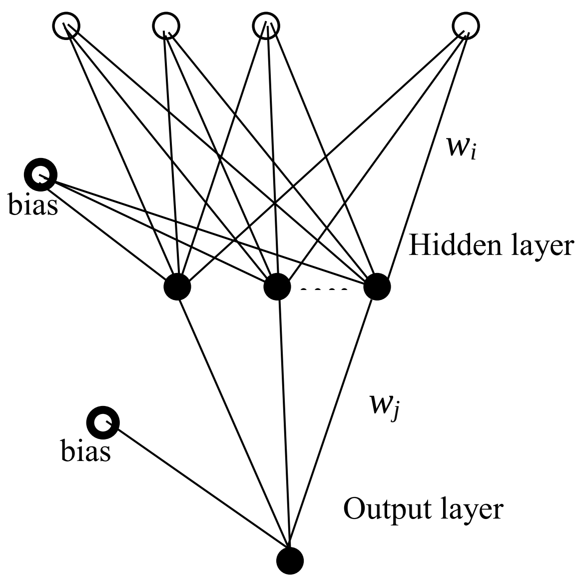


Figure 1: The neural networks architecture.

The operator is defined using a multi-layer perceptron neural networks structure. We constructed 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 is used.

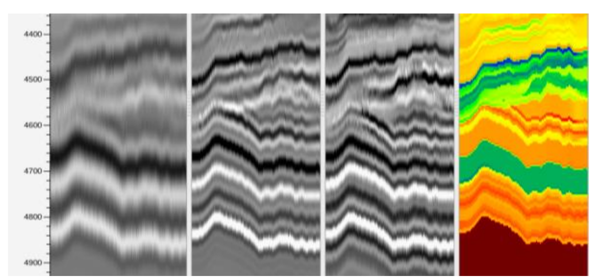
Note that the training dataset is constructed using a running window of length *n* to define input-desired output pairs within each input trace. We found that constructing of the algorithm this way is very powerful for seismic data processing procedures. It enables generalization of the problem by providing a very large set of training examples on the one hand while also acknowledging the convolution model.

To enable spectral broadening we add various seismic attributes as additional inputs. Attributes such as instantaneous frequency and instantaneous phase add information and flexibility to the network and improves its resolution power.

Examples

All examples presented here used stacked 3D seismic data. Training was done on one line and applied to the entire 3D volume. The line displayed in the examples is not the same line used for training. This was done to demonstrate the generalization power of this algorithm.

The first example (figure 2) is a synthetic example, but we used a real seismic project to build this example. First we built an impedance model using real well logs and real structure. We interpolated impedances from well logs following the horizons using kriging (Figure 2.d). So our impedance model contains high frequencies as measured in the well log data. Then we created two synthetic dataset from the impedance model, each one using a different wavelet. Figure 2.a shows the synthetic dataset created with a low frequency wavelet (5-10-20-30 Hz) and Figure 2.b shows the synthetic dataset created with a higher frequency wavelet (5-10-40-50 Hz). This is a major difference in the frequency content. Still we tried to train dataset a) to look like b) the results is displayed in c). In other words, c) is the result of applying the neural networks operator to a), hence, spectral broadening resulted. Figure 3 shows the amplitude spectrum of the three datasets.



a) Input b) Desired Output c) Output d) Impedance Model

Figure 2: Spectral broadening from 10-20 Hz to 10-40 Hz

A second example was created in similar way, but is more moderate in its spectral broadening ambition. Here the input data (Figure 4.a) was created using a band-pass wavelet with 0-20-40-60 Hz and the desired output (4.b) was created using a bandpass wavelet with 0-20-50-70 Hz. c) is the result of applying the neural networks operator to a), and again shows impressive spectral broadening. Figure 5 shows the amplitude spectrum of the three datasets.

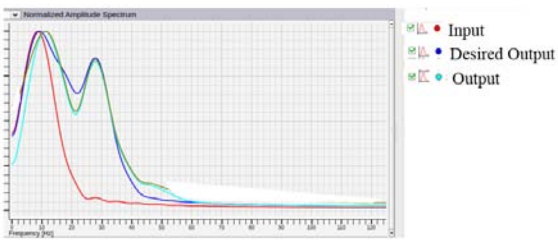
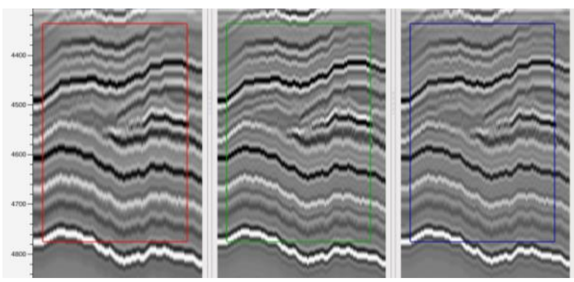


Figure 3: Amplitude spectrum of a), b) and c) from Figure 2.



a) Input b) Desired Output c) Output

Figure 4: Spectral broadening – construction of the synthetic examples

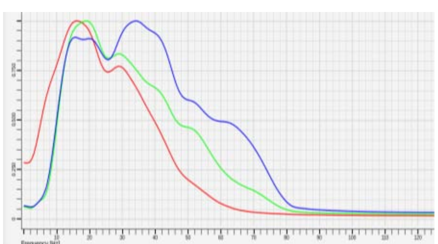
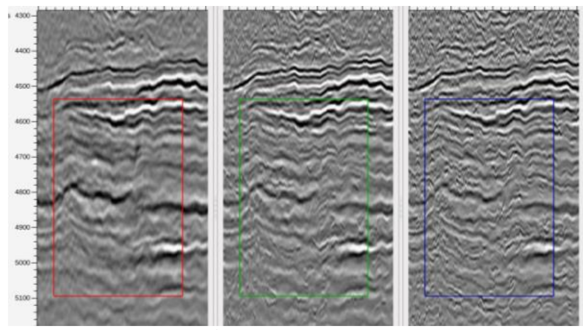


Figure 5: Amplitude spectrum of a), b) and c) from Figure 4.

We constructed this synthetic example from a stack of a real 3D data and used the wavelet extracted from that real dataset. We then also applied the resulting neural networks operator to the real input data attempting to broaden its frequency spectrum using the operator derived from the synthetic training set. The results are presented in Figure 6. Figure 6.a is the input data, 6.b is the frequency enhanced dataset and 6.c is a different result derived using the same synthetic example but with a larger set of seismic attributes included in the operator contraction. We can see that with additional attributes we achieved greater effect, i.e., broader frequency spectrum. The frequency spectrums associated with Figure 6 are displayed in Figure 7.



a) Input b) Frequency range broadening c) Frequency range broadening using more attributes

Figure 6: Spectral broadening applied to real data

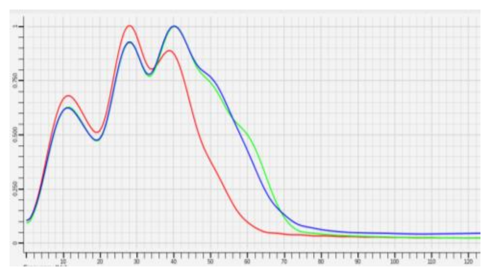


Figure 7 Amplitude spectrum of a), b) and c) from Figure 6. Colors are matching the color of the regions marked in Figure 6

Conclusions

We showed that an artificial intelligence approach to solving seismic problems creates new opportunities in seismic data processing and interpretation. Specifically we showed that when using a learning process based on synthetic examples, neutral networks algorithms can be used to broaden the seismic frequency spectrum..

We plan more research into this approach for increasing the frequency content of seismic data with more sophisticated constructions. We also plan to use this neural networks construction for solving additional problems in seismic data processing and interpretation.

EDITED REFERENCES

Note: This reference list is a copyedited version of the reference list submitted by the author. Reference lists for the 2017 SEG Technical Program Expanded Abstracts have been copyedited so that references provided with the online metadata for each paper will achieve a high degree of linking to cited sources that appear on the Web.

REFERENCES

Calderon, M., 2000, Artificial neural networks for parameter estimation in Geophysics: Geophysical Prospecting, **48**, 21–47, http://dx.doi.org/10.1046/j.1365-2478.2000.00171.x.

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

Zakhem, U., Canning, A., and Litvin, A., 2003, 4-D cross-equalization and offset equalization using a Neural Networks approach: 73rd Annual International Meeting, SEG, Expanded Abstracts, https://doi.org/10.1190/1.1817586.