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Multiple Reflection Attenuation in Marine Seismograms using Backpropagation Neural Networks

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keywords: *multiples neural networks*

ABSTRACT

Multiple reflections in seismic data are generally considered as unwanted noise that often seriously impedes correct mapping of the subsurface geology in search of oil and gas reservoirs. We train a backpropagation neural network in order to recognize and remove these multiple reflections and thereby bring out the primary reflections underneath. The training data consist of model data containing all multiples and the corresponding seismic sections containing only the primary arrivals. Basis for the modeling are data from a real well log that is typical for the area in which the data were gathered. In contrast to existing conventional deconvolution methods, the neural network does not depend on such restricting assumptions concerning the underlying model as, for example, the Wiener filter, and it has the potential to be successful in cases where other methods fail. A further advantage of the neural net approach is that it is possible to make extensive use of a-priori knowledge about the geology which is present in the form of well log data. Tests with realistic data show the ability of the neural network to extract the desired information.

MULTIPLES AND NEURAL NETWORKS

In seismic exploration the problem of multiple reflections contaminating the seismograms and thus disguising important information about subsurface reflectors is well-known but yet unsolved. Especially in marine exploration the water layer often behaves as a wave trap, where waves are multiply reflected between the sea surface and the sea bottom. Waves that are transmitted through the seabottom can also reverberate between deeper reflectors. The energy of these interbed multiples and the water layer reverberations can become so strong that the primary reflection arrivals of deeper target reflectors become completely invisible. For correctly locating a target reflector an oil reservoir is expected underneath, these disturbing multiple reflections have to be eliminated.

Today, seismic signal processing often still is based on very simple linear models, whose theory rests on assumptions that are often not met in practice. An example is

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seismic deconvolution with Wiener filters, a method that tries to predict multiples and subtract them from the seismic trace. This method suffers from some limitations such as, for example, if the stratigraphy itself is periodic, it is predicted by the algorithm and removed along with the multiples (Robinson and Treitel, 1980). Nevertheless, these traditional methods are implemented very successfully in many cases, but there is a variety of cases where they fail.

The neural network does not depend on such restricting assumptions concerning the underlying model and has the potential to work in areas where conventional methods fail. It is adaptive and able to learn highly non-linear interrelations in the data, should they exist. A further advantage of neural nets is that they are able to make extensive use of a-priori knowledge about the geologic subsurface structure which exists in the form of velocity and density logs from a borehole. So far the number of applications in geophysics is limited. One of the first fields was first break picking (McCormack, 1991), but also inversion (Roeth, 1993) and deconvolution (Wang and Mendel, 1992). We show the application of an artificial neural network on seismic deconvolution with emphasis on multiple elimination on a set of data modeled on the basis of a real well-log.

The neural net input is the seismic trace containing all kinds of multiple reflections and the desired output is the seismic trace with only the primary reflection events. The neural net output gives the arrival times as well as the reflection strengths of the desired primary reflections (see Figure 1). However, the amplitude characteristic of the seismic wavelet is destroyed. Thus, this method is not applicable if in a following processing step the true amplitude of the seismic trace is required, although the reflection strength of the individual reflectors are reproduced quite reliably.

Instead of using the standard backpropagation learning algorithm we employed the RPROP (resilient propagation) algorithm (Riedmiller and Braun, 1993) which shows considerably faster convergence.

The results of training a neural network with several seismic sections (CMP-gathers) is shown in Figure 2. The gather on the left is the test input for the neural net (CMP-gather containing the full wave field), the gather on the right represents the desired output (CMP-gather containing only primary arrivals) and the gather in the middle is the actual output of the neural net for the test input. Obviously, the multiples are suppressed to a certain extent and primary information that was previously invisible is revealed.

CONCLUSIONS

The neural net is able to produce the main features of the desired primary reflections out of the pre-stack seismic data for a seismic section and thus the results suggest that the neural net approach to deconvolution or multiple removal is a promising method, especially since it can handle easily non-linear data interrelations. The quality varies since the neural net generalizes from the input of relatively few seismograms and it tries to remove multiple energy based on empirically learned rules. In the case of zero-offset

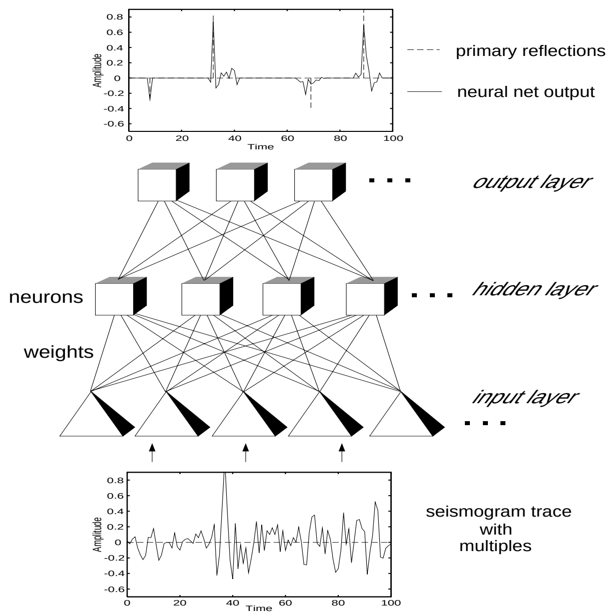

Figure 1: Training of the neural net: Presentation of the training set consisting of 100 seismic traces containing all kinds of multiple reflections at the input layer and simultaneously providing the desired output, i.e. the arrival time and reflection strength of the primary reflections.

data the neural net method proved to be able to reveal the desired information even in the case of data heavily corrupted by noise. The performance decreases with decreasing signal-to-noise ratio. Further investigations are necessary to determine the degree of confidence with which primary reflection events are unmasked in the process. We also might investigate if there exist domains or data representations in which the neural net can learn and generalize more easily.

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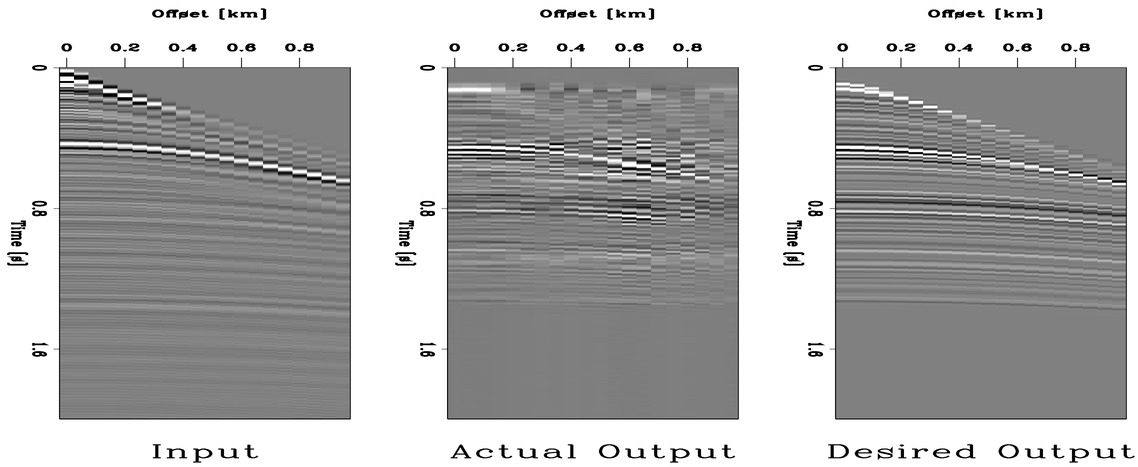

Figure 2: Input, actual output, and desired output for the synthetic test pattern. Two deep reflectors have been revealed by the neural net.

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PUBLICATIONS

Detailed results were published by (Essenreiter, 1996) and (Essenreiter et al.,).