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Section 0.0 Abstract

Least-squares inverse filters have found widespread use in the deconvolution of seismograms and the removal of multiples. The use of least-squares prediction filters with prediction distances greater than unity leads to the method of predictive deconvolution which can be used for the removal of long path multiples.

The predictive technique allows one to control the length of the desired output wavelet by control of the predictive distance, and hence to specify the desired degree of resolution. Events which are periodic within given repetition ranges can be attenuated selectively. The method is thus effective in the suppression of rather complex reverberation patterns.

A back propagation(BP) neural network is constructed to perform the detection of first arrivals of the multiples and therefore aid in the more accurate determination of the predictive distance of the multiples. The neural detector is applied to synthetic reflection coefficients and synthetic seismic traces. The processing results show that the neural detector is accurate and should lead to an automated fast method for determining predictive distances across vast amounts of data such as seismic field records. The neural network system used in this study was the NASA Software Technology Branch's NETS system.

Section 1.0 Introduction

The Wiener filter (least-squares inverse filter) is one of the most effective tools for the digital reduction of seismic traces. It is the most important element of many deconvolution methods. In one application this filter is used to deconvolve a reverberating pulse train into an approximation of a zero-delay unit impulse. More generally it is possible to arrive at Wiener filters which remove repetitive events having specified periodicity. Multiples are such events and the periodicity are the arrival times or "predictive distances" of the multiples.

In this paper we develop a method using the BP neural network to detect multiples and their first arrivals. This would enable us to automatically determine predictive distances for each seismic trace and thus remove multiples more accurately and with a minimum effect on good data. The neural detector is applied to synthetic reflection coefficients and synthetic seismic traces. The processing results show that the neural detector is accurate and should lead to an automated fast method for determining predictive distances across vast amounts of data such as seismic field records. The neural network system used in this study was the NASA Software Technology Branch's NETS system.

Section 2.0 Synthetic Data: Reflection Coefficients

Figure 1. represents an idealized noise-free model of an offshore seismic situation (Peacock and Treitel, 1968). Reflector 1 is the water surface, reflector 2 is the water bottom, reflector 3 is a strong interface beneath the water bottom, and S is the surface location just beneath the water surface. The associated normal incidence reflection coefficients are 1, c_1 , and c_2 , respectively, while the transmission coefficient across reflector 2 is t_1 . If c is the downward reflection coefficient, the corresponding upward reflection coefficient is $-c$. From physical considerations, we know that the magnitude of all reflection coefficients are less than unity. Figure 2. shows the deconvolution of a first-order ringing system

$$(1, 0, 0, \dots, n, 0, -c_1, 0, 0, \dots, n, 0, c_1^2, 0, 0, \dots, n, 0, -c_1^3, 0, 0, \dots, n, 0, c_1^4, 0, 0, \dots, n, 0, \dots) \dots \dots \dots (I)$$

where n is the predictive distance. The deconvolution operator that removes the multiples $(-c_1, c_1^2, -c_1^3, c_1^4)$ is $(c_1, 0, 0, \dots, n, 0, 1)$. The results after deconvolution is the multiple free signal $(1, 0, 0, \dots, n, 0)$.

Figure 3. shows the deconvolution of a second-order ringing system

$$(1, 0, 0, \dots, n, 0, -2c_1, 0, 0, \dots, n, 0, 3c_1^2, 0, 0, \dots, n, 0, -4c_1^3, 0, 0, \dots, n, 0, 5c_1^4, 0, 0, \dots, n, 0, \dots) \dots \dots (II)$$

where n is the predictive distance. The deconvolution operator that removes the multiples $(-2c_1, 3c_1^2, -4c_1^3, 5c_1^4)$ is $(c_1^2, 0, 0, \dots, n, 0, 2c_1, 0, 0, \dots, n, 0, 1)$. The results after deconvolution is the multiple free signal $(1, 0, 0, \dots, n, 0)$.

We simulated the neural detector for the above synthetic seismic trace (I) above by training an NN with data of the form $(-c_1, c_1^2, -c_1^3, c_1^4)$, $0 < c_1 < 1$, as input where +0.5 indicated a multiple, and with data not of the form $(-c_1, c_1^2, -c_1^3, c_1^4)$, $0 < c_1 < 1$, as input where -0.5 indicated an event that is not a multiple. The topology of the NN is shown in Figure 4. The network has four input nodes, two hidden nodes, and one output node. An example of training input indicating a multiple is $(-0.5, 0.25, -0.125, 0.0625)$ for input and +0.5 for output. An example of training input indicating a non-multiple is $(-0.5, 1.25, -0.145, 0.1117)$ for input and -0.5 for output. Another example of training input indicating a non-multiple is $(2.0, -0.5, 0.25, -0.125)$ for input and +0.5 for output. This last example would simulate a window moving over a multiple but not quite covering the multiple. We trained the network with 5 multiples and 5 non-multiples and achieved 100% accuracy for 30 test cases.

We performed a similar experiment for a second-order ringing system and also achieved 100% accuracy.

Section 3.0 Synthetic Data: Seismic Data

Marine seismic data are frequently plagued by the presence of multiple reflections from the water bottom and by water-layer peg-leg multiples. This problem is especially severe in "hard bottom" areas where the reflection coefficient at the water-sediment is large, resulting in high-amplitude multiple reflections. Essentially, the water-bottom multiples arise because the water layer acts as a wave guide, resulting in repetitions of the water-bottom bounce. The peg legs arise from primary reflections that take an extra bounce or two in the water layer. There are two approaches to suppression of multiples, each depending upon one of the two distinguishing characteristics of multiples, namely periodicity and velocity.

At shallow water depths (say, less than 250 ft.) the multiples are periodic, after normal moveout(NMO) correction, with a repetition period equal to the two-way travel time through the water layer. Predictive deconvolution is very effective in suppression of such multiples.

When the water is deep, successive multiples are no longer periodic at far offsets, nor do they have the proper amplitude relations for predictive deconvolution to be successful. However, multiples typically spend more of their travel time in the lower velocity water layer than the primaries do, and as such have lower velocities. The differential moveout between multiples and primaries caused by the difference in their velocities has been successfully exploited in the common depth point (CDP) stacking scheme, as well as in exponential stacking routines.

At intermediate water depths (250 -1250 ft.) the multiples are not periodic, nor is the velocity difference between the primary and its associated (peg legs) multiples sufficient to allow for the application velocity-separation schemes mentioned above. The non periodicity of the multiples is shown on a synthetic field record in Figure 5, where the spread is over

10,000 feet and the two-way water-bottom time is 200 msec. The two-way travel time to the primary is 1 second, and the velocity of the primary event is 6000 feet/second. Notice that on the near trace the period of the (peg leg) multiples is 300 msec, whereas on the far trace the multiples are no longer periodic. This synthetic field record confirms the lack of periodicity of the multiples at a large offset, which precludes the use of conventional deconvolution schemes. Deconvolution schemes operate with a specified distance dependent upon the time span between a primary and its first multiple, and this time span is assumed to apply between successive multiples.

Observing that (peg-leg) multiples on intermediate water depths are no longer periodic with increasing offset Hilderbrand(1978) proposed a non periodic form of prestack gapped deconvolution to attenuate (peg leg) multiples. This report uses synthetic data to demonstrate the feasibility of such a deconvolution procedure being improved upon and extended to deep water depths using a neural network to determine the predictive distance for multiples. Extensive recording of a program originally coded by Hildebrand would be required.

Section 3.1 Description of The Synthetic Seismic Traces.

1) The "water layer" model(field record) was created by generating spikes with a normal move-out equation and a model velocity of 5000 feet per second. The reflection coefficients were determined by the equation

$$r = (V1 - V2)/(V2 + V1), \text{ neglecting density.}$$

The half spaces were assumed to have velocities of 1100 ft./sec.(air) and 6500 ft./sec/ (rock). The data is sampled every two milliseconds. Convolution of the spikes(reflection coefficients) with a minimum phase wavelet produced the final seismic trace(see Figure 6.). The first trace of the primary starts at 200 msec and extends to 300 msec. The first trace of the first multiple starts at 400 msec and extends to 500 msec. The first trace of the second multiple starts at 600 msec and extends to 700 msec(the second multiple is faint). We trained a BP network with 70 input nodes, 20 hidden nodes, and 2 output nodes to detect the multiples. Traces 1, 3, 5, 10, and 15 were input as part of the training data. The first 70 samples from each trace multiple were used. For the output nodes, true was indicated as +0.5 and false was indicated as -0.5. Five traces that were not multiples were generated and entered as training data in a similar manner. This gave the network a grater training scope. For test data we entered the first 70 samples of the remaining multiples and five new non multiple examples. We created one network for the first-order multiples and a second network for the second-order multiples. We achieved 100% accuracy in both tests.

2) The Three-Layers Model (20 trace field record) data were generated by a wave-equation program (PARX) at Texaco, Incorporated. The assumed reflection times (at zero-offset) were 350 msec, 500 msec, and 750 msec. The velocities of the three rock formations were 5000 ft./sec., 6500 ft./sec., and 9500 ft./sec., respectively(see Figure 7).

The three primaries start at 400, 500, and 750 milliseconds, respectively. The three corresponding first-order multiples start at 1200, 1450, and 1650 milliseconds, respectively. The topology and setup of the network was the same as in the "water layer" model. We worked only with first-order multiples. Three networks were created for each of the three different primaries' respective multiples. We achieved 100% accuracy in all three tests.

The topology for the above networks is shown in Figure 8.

Section 4.0 Mathematics Of Gapped, Predictive Deconvolution.

For zero-offset traces, and for normal incidence ray paths, peg legs from a primary reflector are periodic, the period being equal to the two-way travel time in the water-bottom(Backus, 1959). Mathematically, the (peg-leg) multiple generation process can be described by the difference equation:

$$m(n) - 2Rm(n-T) - (R^2)m(n-2T) + p(n)$$

where

n = sample number for some fixed sampling interval
 m = composite(primary + pegleg) signal received
 R = water-bottom reflection coefficient
 T = two-way travel time in water layer in samples
 p = primary signal giving rise to peg leg) multiples

and,

$$p(n) = m(n) + 2Rm(n - T) + (R^2)m(n - 2T).$$

The primary p(n) can be recovered, theoretically, from a weighted sum of the trace and its delayed samples. This is an finite impulse response operator with two gaps of T each-hence the terminology "double gapped " operator. Non periodic models of p(n) and m(n) have been postulated where both m(n) and p(n) are functions of T1 and T2 where T1 is the separation between primary and first (peg-leg)multiple in sample intervals, and T2 is the separation between (peg-leg)first multiple and second (peg-leg) multiple in sample intervals. If T1 = T2, this later model collapses to the periodic (peg-leg) multiple model.

The arrival time of the (peg-leg) multiples can be computed using Dix's formula in intermediate water depths. Applications have shown many inaccuracies in intermediate depth water. It is even recommended not to use this approach in deep water due to inaccurate calculations of T1 and T2, the predictive arrival times for the (peg-leg) multiples. Our feasibility study suggests that the predictive arrival times can be found automatically by identifying the multiples with a neural network. We could approximate the location of the multiples with Dix's equation, and fine tune their location with the neural networks.

Section 5.0 Summary

Neural Networks are now part of the leading edge in Geophysical data processing and interpretation. They have been recently successful in locating subsurface targets (Poulton, et al, 1992) and in obtaining seismic reflectivity sequences from seismic data(Wang, 1992). In this study we have shown the feasibility of developing a BP neural network for estimating the predictive distances of multiples where other traditional methods are not as adequate as desired. This seems to be particularly true in the case of deep water bottom multiples. The simulation data processing results showed that 1) the accuracy of the predictive distance of multiples can be enhanced with use of a neural detector over existing methods, and 2) the software implementation could be much faster since NN applications are potentially faster than traditional numerical and statistical methods. We look forward to the opportunity to implement an NN application and apply it to real data.

FIGURES

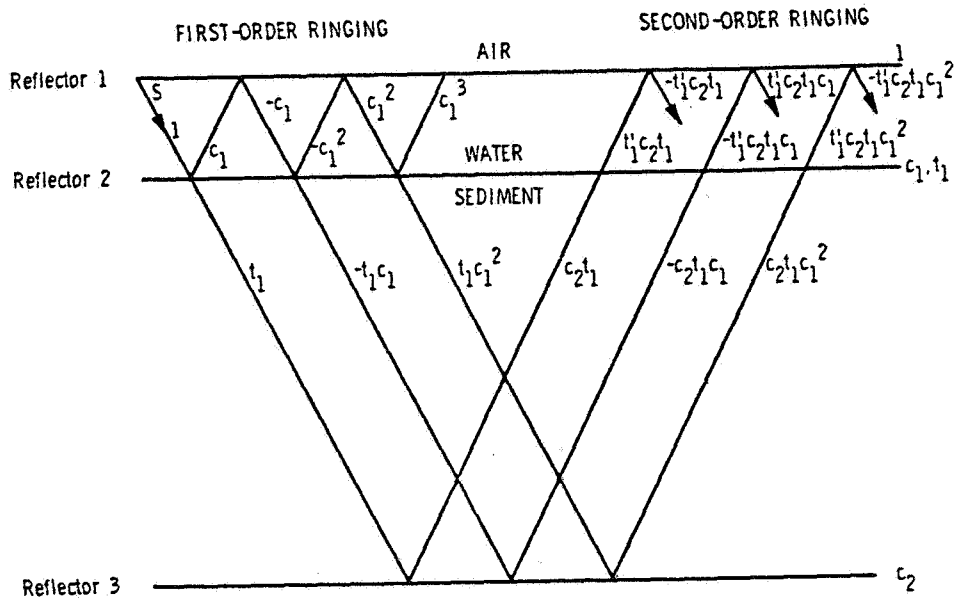


FIG. 1. First- and second-order ringing in a 2-layer marine model.

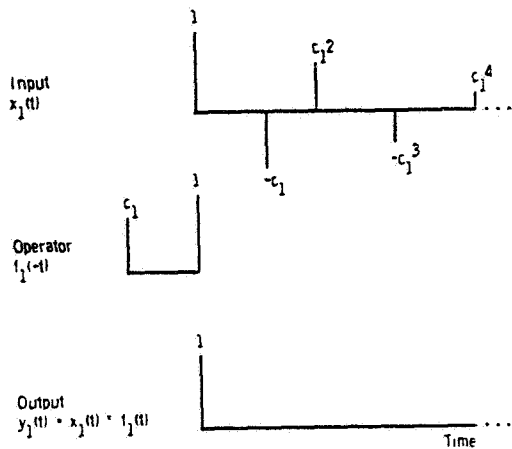


FIG. -2. Deconvolution of a first-order ringing system. The operator is shown in time-reversed form.

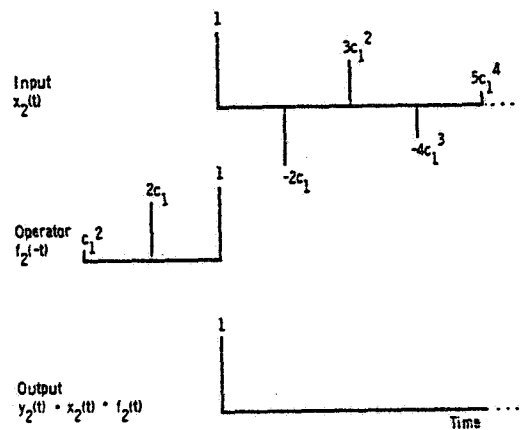


FIG. 3. Deconvolution of a second-order ringing system. The operator is shown in time-reversed form.

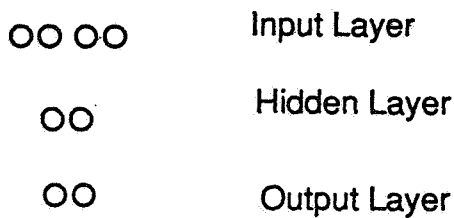


Figure 4. NN Topology For The Reflection Coefficients Data

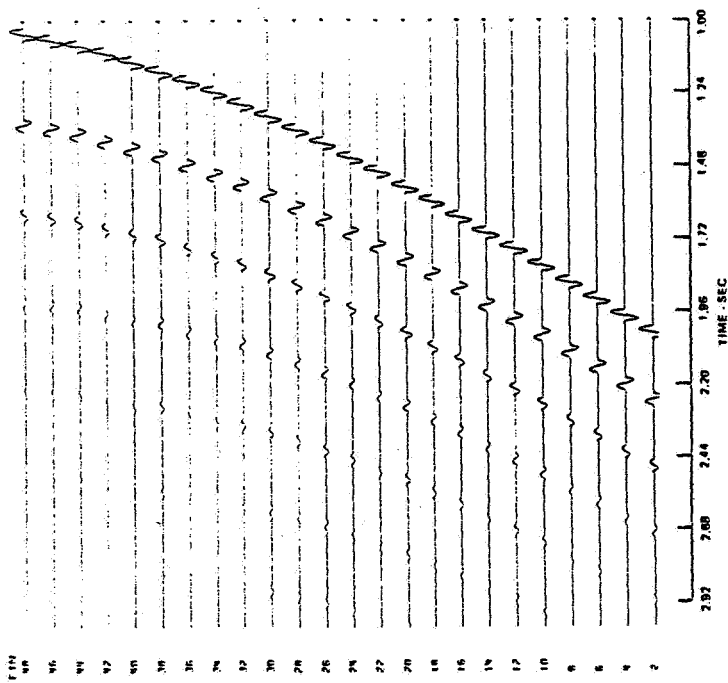


Figure 5. Synthetic gather with primary and multiple reflections

WATER-MODEL

3-LAYERS

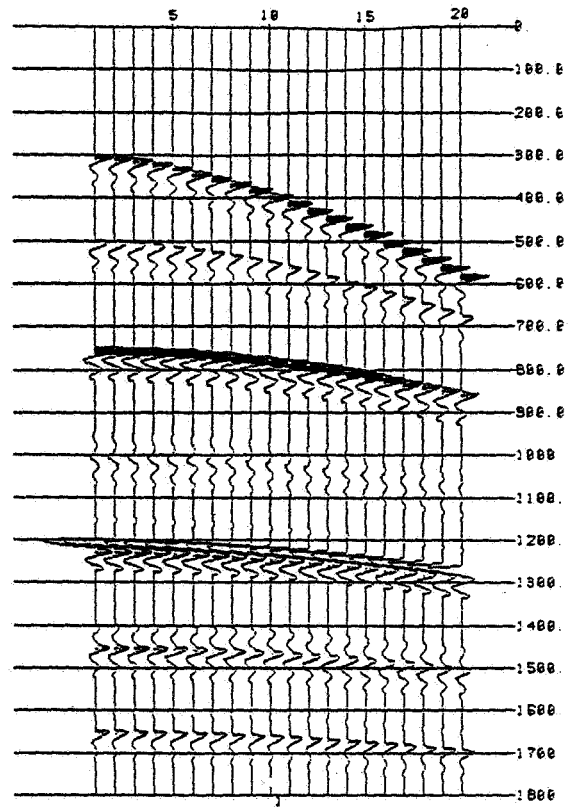
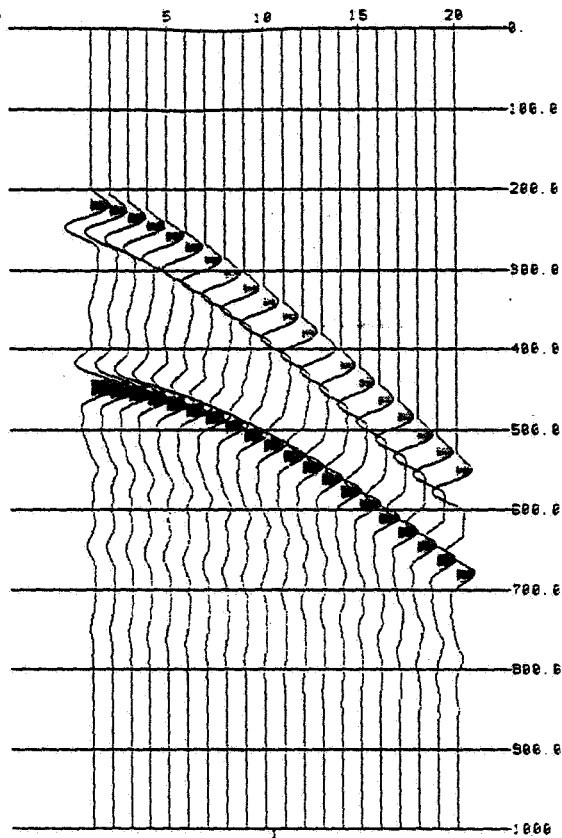


Figure 6. Water-Layer Model of a 20 Trace Field Record

Figure 7. Three Layer Model of a 20 Trace Field Record

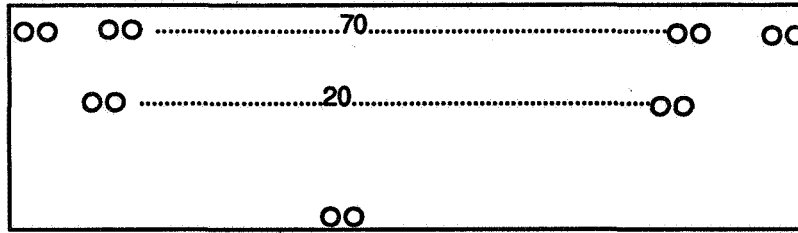


Figure 8. Network Topology For Multiple Detection BP Network on Synthetic Seismic data

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