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Model-based subtraction of multiple events

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ABSTRACT

Attenuation (if not complete elimination) of multiple reflections is one of the important tasks to be performed when processing seismic data. Interpretation of the data, or of extracted attributes such as AVO, requires the amplitude of the signal to be preserved by the attenuation process. I present in this study a method that achieves this aim. The method requires a model of the multiples present in the dataset. The algorithm is based on the spatial predictability of the events that form the signal and the multiple noise. Under this predictability assumption interferences between primaries and multiples can be resolved, irrespective of the possible spatial aliasing of some events in the dataset.

INTRODUCTION

Most of the techniques used daily in data processing utilize some property that differentiates primary from multiple reflections (periodicity, normal moveout) in order to reject the unwanted signals from the seismic traces. These techniques are mostly filtering techniques and can adversely affect the amplitude of the primaries when primaries and multiples strongly interfere.

An other class of techniques involves modeling and attenuation of a particular family of multiple events. Doicin and Spitz (1991) described perhaps the most obvious technique in this class to attenuate peg legs generated by a strong impedance contrast and reverberating between the free surface and a uniform sea floor. Verschuur et al. (1992) constructed all the free surface multiples using a convolution technique that transforms primaries in multiples and multiples into a higher order multiples. Araujo et al. (1994) described a technique that predicts all multiples, including interbed multiples. All these attenuation techniques have a property in common: the modeled multiples and the actual ones differ, in the best case, by a wavelet. The subtraction of the modeled events from the seismic data is performed using an adaptation process, based on the minimum energy assumption. However, it is easily shown (Claerbout, 1992, Spitz, 1999) that this adaptation cannot preserve the amplitude of the primaries when primaries and multiples interfere.

This paper assumes that a model of the multiple reflections is available and focuses on the subtraction issue. In particular, it is shown that multiples can be perfectly removed from a gather under two assumptions. (1) The primary and multiple events are spatially predictable. (2) The number of events that form the signal and the number of events that form the noise are known.

THE MODEL-BASED SUBTRACTION PROBLEM

The synthetic gathers displayed in the figure 1 illustrate the general problem of separating signal events from noise events in a gather when a model of the noise is given. The gather (a) is made of three different events: the signal (the dipping event that appears at the earliest time on the first trace) and two noise events. In vector notations, if **D**(f) is the vector that represents this dataset at the temporal frequency f, then:

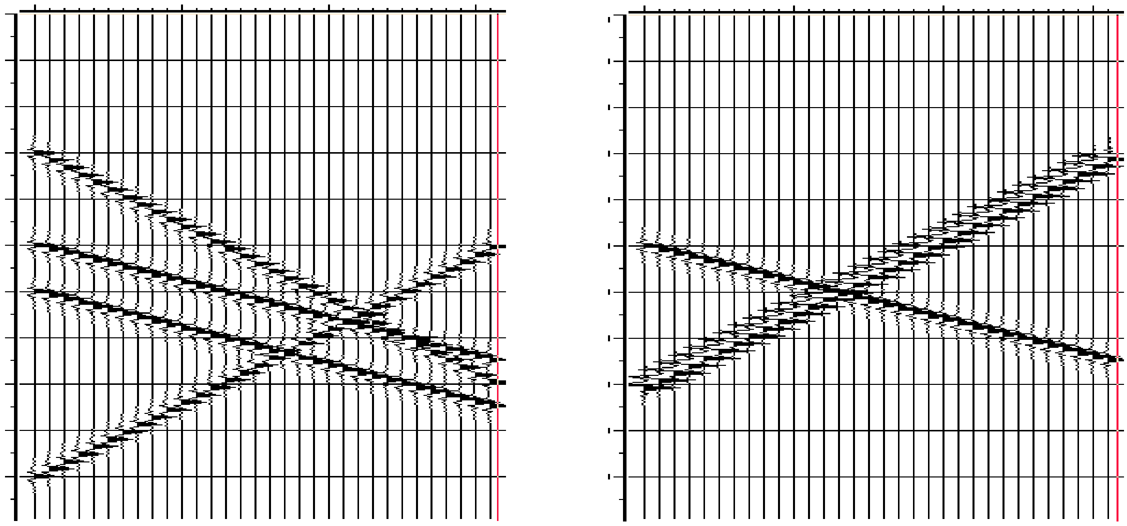
$$\mathbf{D}(f) = a(f)\,\mathbf{S}(f) + b_1(f)\,\mathbf{N_1}(f) + b_2(f)\,\mathbf{N_2}(f) \quad . \qquad (1)$$

Here $\mathbf{S}(f)$, $\mathbf{N_1}(f)$ and $\mathbf{N_2}(f)$ stand respectively for the patterns (vectors that translate the phase shift and the amplitude change from one trace to the next) of the signal and of the two noise events at the temporal frequency f of the bandwidth. $a(f)$, $b_1(f)$ and $b_2(f)$ denote respectively the waveforms of the signal and of the noise events. Remark that it is not the pattern, but the waveform that characterizes the two parallel noise events in figure 1(a). The noise component of the gather can be removed without affecting the signal only if the three patterns in the expression (1) are known. While this is possible on the present synthetic, (the apparent velocities can easily be measured) the patterns cannot be provided in general situations since it implies a perfect knowledge of the signal itself.

Consider now the particular model of the noise shown in the figure 1(b). This gather can be written as following:

$$\mathbf{M}(f) = c_1(f)\,\mathbf{N_1}(f) + c_2(f)\,\mathbf{N_2}(f) \quad . \qquad (2)$$

Since the patterns $\mathbf{N_1}$ and $\mathbf{N_2}$ are the same as in (1), **M** is an exact model of the noise in the original gather **D**. One can wonder first at the utility of this particular model. It is shown in the next section that giving an exact model, no matter how “different” from the actual noise, can actually solve the subtraction problem.



(a) (b)

Figure 1 – A synthetic example. (a): the input gather. (b): a particular model of the “noise” events.

SPATIAL PREDICTABILITY

Spatial predictable filters in the f-x domain have been introduced in seismic data processing by Canales (1984) to attenuate random noise. The properties of such filters have been utilized by Spitz (1989) and Claerbout (1992) to de-alias that part of the data that is spatially predictable. In a few words, if a dataset **D** is made of K spatially predictable events (linear events, for instance), the dataset defines at each frequency f in the band the prediction error filter (p.e.f.) **P**:

$$P_K(f)\, D_{i-K}(f) + \ldots + P_1(f) D_{i-1}(f) - D_i(f) = 0 \quad . \qquad (3)$$

The coefficients of the filter are the coefficients of the polynomial:

$$(z-z_1)\,(z-z_2)\,\ldots\,(z-z_K) = 0 \quad , \qquad (4)$$

where $z_1, \ldots z_K$ are the (constant) amplitude changes and phase shifts of the K events at the frequency f. Therefore, the gather in the figure 1(a) is predictable with a 3 terms prediction filter. The filter components are the coefficients of the polynomial $(z-z_s)(z-z_1)(z-z_2)$. The gather in the figure 1(b) is also spatially predictable, but with a 2 terms prediction filter. Its coefficients are the coefficients of the polynomial $(z-z_1)(z-z_2)$. It follows that if **P**(f) is the p.e.f. computed from the input gather 1(a) and **Q**(f) the p.e.f. computed from the noise model 1(b), the p.e.f. **R**(f), that concerns only the predictable part of the signal, is found by deconvolving **P** with **Q**. Without any other information than the number of predictable events in the input and in the model gathers, the deconvolution provides, at each frequency f, the p.e.f. of the events that form the signal.

THE P.E.F. DEFINED SUBTRACTION

The knowledge, at each frequency, of the p.e.fs of the signal and of the noise allows the separation of these components even in case of strong interference. Let in general, the signal and the noise be made respectively of K and L predictable events, that define the p.e.fs **R** and **Q** respectively.

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$$\mathbf{D}(f) = \mathbf{S}(f) + \mathbf{N}(f) \qquad (5)$$

Since the output of a p.e.f. on a predictable gather is zero, the signal component in (5) can be constructed from the following equations system:

$$\mathbf{Q}(f)\ \mathbf{S}(f) = \mathbf{Q}(f)\ \mathbf{D}(f) \qquad (6a)$$

$$\mathbf{R}(f)\ \mathbf{S}(f) = \mathbf{0} \qquad (6b)$$

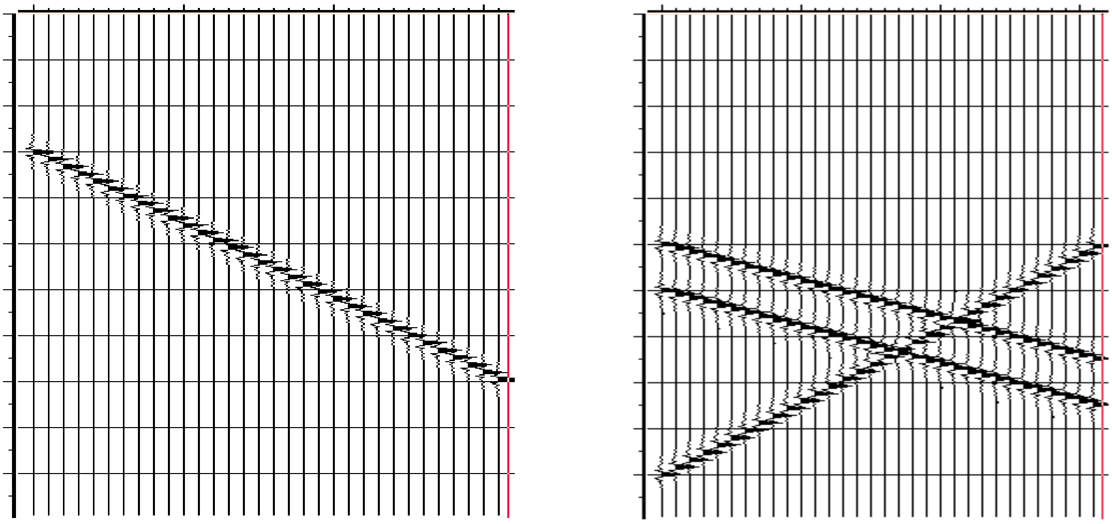
A more evolved subtraction method involves pattern recognition. The signal is a vector **S** in a K-dimensional space, and the noise an other vector, **N**, in a L-dimensional space The p.e.f. **R** and **Q** contain all the information on the patterns of the signal and noise events. Indeed, it is always possible to construct a particular basis of the signal space starting with the p.e.f. **R** and an other particular basis of the noise space starting with the p.e.f. **Q**. Let these bases be denoted respectively by **U** and **V**.

$$\mathbf{S}(f) = c_1(f)\ \mathbf{U_1}(f) + \ldots + c_K(f)\ \mathbf{U_K}(f) \qquad (7a)$$

$$\mathbf{N}(f) = d_1(f)\, \mathbf{V_1}(f) + \ldots + b_L(f)\, \mathbf{V_L}(f) \tag{7b}$$

The separation of signal and noise can be easily made and involves the estimation,in the least squares sense, of the waveforms $c_1, \ldots, c_K$ at all the frequencies in the band.
When a correct model of the multiples to be subtracted is available, the pattern recognition algorithm in the the f-x domain is made of the following four steps:

(i) Estimate the p.e.fs **P** and **Q** from the input and model gathers respectively.
(ii) Deconvolve the p.e.f. **P** with **Q** to get the p.e.f. **R** that characterizes the behavior of the signal.
(iii) Construct two particular bases that span respectively the signal and the noise spaces.
(iv) Perform the separation in the least squares sense.



(a) (b)
Figure 2. Separation of signal and noise (a): the signal component (b): the noise component

Figure 2 shows the output of this model-based decomposition method on the gather 1(a). The decomposition is perfect, although some events are spatially aliased.

DISCUSSION

The first requirement of the technnique described above is the availability of a “correct” model of the targeted multiple reflections. Such a model may be difficult to construct. The actual modeling techniques that are based only on the recorded data imply a perfect 2-D earth (no out of plane multiples) and a perfect 2-D acquisition (no cable feathering). On the other hand, models based on a velocity model assume that this velocity model is perfectly known and that the amplitudes are correctly processed as well, requirements hardly met on real data.
The theoretical requirements assume the gathers spatially predictable, and the number of present events known. Certainly, the predictability assumption may seem rather strong, when thinking in terms of events that display constant moveouts (linear events). In fact, it can be shown that the class of predictable events is rather large, much larger in fact than that of linear events. The problem of finding the optimal lengths of the prediction filters, directly related to that of the number of events, is more difficult to solve, simply because these lengths can be frequency dependent. While it is possible to define an algorithm that estimates these optima, its implementation would result in prohibitive computing times. These assumptions are identical to those characterizing the attenuation of random noise in the f-x domain, a technique widely used in processing centers worldwide. Most of the time, the lengths of the prediction filters are time and sspace invariant and involve some educated guess.
A drawback of this pattern recognition technology is clearly seen in the synthetic example analyzed above. The technology does not allow to distinguish between conformal events (events that display the same pattern). If perchance a multiple and a primary are conformal in a processing window, that primary will be removed by the process. In that case processing in one domain rather than another (such as CMP domain rather than offset domain) may decrease the probability of such occurrence. A safer procedure consists in generalizing the f-x domain technique to the f-xy domain. The rationale behind such generalization is that the probabilities of finding a multiple conformal with a primary both in-line and cross-line are much lower than a possible conformity in only one direction.
It is indeed difficult to define any technique that has no drawbacks. In this respect, the technique described in this paper is no exception. Experience with synthetic and real data shows that the technique is robust and reasonably economical.

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