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Applying SEP's latest tricks to the multiple suppression problem

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ABSTRACT

Two methods for suppressing multiples are proposed. In the first, multiple suppression is expressed as a signal to noise separation problem. The problem is solved in the time domain using space-varying Prediction Error Filters (PEFs). The second method shows how greater separation between primaries and multiples can be obtained by velocity space inversion using a Huber functional rather than the standard L_2 functional. Early results of both methods are encouraging.

INTRODUCTION

Multiple suppression is one of the biggest problems facing the seismic industry. Methods that have proven effective in 2-D are either cost-prohibitive or not easily extendible into 3-D (Berkhout and Vershcuur, 1997; Vershcuur and Berkhout, 1997; Sun, 1999). Spitz (1999) proposed forming the multiple suppression as a signal-to-noise separation in the frequency domain, but this method suffered from stability problems.

Until recently, an equivalent time domain method was not possible. Claerbout(1998) discovered that multi-dimensional time filters can be mapped into 1-D, therefore making it possible to do inverse filtering. Crawley et al. (1998) showed how non-stationary filters could more accurately predict seismic data. Fomel (1999) demonstrated how Spitz's method could be changed to work with time domain PEFs.

In the first section of the paper, we perform time domain multiple suppression by a two step method. We first estimate a space-varying PEF from data (a CMP gather) and a noise model (an estimate of the multiples obtain by downward continuing through the water column twice). We then separate out the signal (primaries) from the noise (multiples) by a simple inversion scheme.

In the second portion of the paper we present a better way to separate multiples in velocity space. Lumley et al. (1994) described a CMP gather as a sum of hyperbolic events. They then inverted this velocity-space transform into (τ,v) space, muted multiples, and transformed back into (t,h) space. Guitton and Symes (1999) showed that a Huber functional (Huber, 1973) produces a velocity scan where reflection energy is better behaved. We invert into (τ,v) using the

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Huber functional, rather than an L_2 functional. We show that the Huber method provides more separation between primary and multiple trends, and therefore improved multiple suppression.

MULTIPLE SUPPRESSION USING SIGNAL-NOISE SEPARATION

Signal to noise separation has a long history at SEP (Harlan, 1986; Kostov, 1990; Claerbout, 1991). The method we use is similar to Abma's (1995) formation. Abma (1995) proposed solving the set of equations:

$$\begin{aligned} \mathbf{Nn} &\approx \mathbf{0} \\ \epsilon \mathbf{Ss} &\approx \mathbf{0} \\ \text{subject to} &\leftrightarrow \quad \mathbf{d} = \mathbf{s} + \mathbf{n} \end{aligned} \tag{1}$$

where the operators $\mathbf{N}$ and $\mathbf{S}$ represent $t-x$ domain convolution with (PEF's) which decorrelate the unknown noise $\mathbf{n}$ and signal $\mathbf{s}$, respectively, and the factor ϵ balances the energies of the residuals. For his problem he assumed that the noise was uncorrelated, therefore $\mathbf{N}$ becomes the identity and $\mathbf{S}$ is the PEF that best predicted the data in a given window [patching approach (Claerbout, 1992; Schwab and Claerbout, 1995)].

In the multiple problem the noise is not uncorrelated so we must find another way to find $\mathbf{N}$. Spitz (1999) proposed defining $\mathbf{S}$ as $\mathbf{S} = \mathbf{DN^{-1}}$ where $\mathbf{D}$ is a filter that characterizes the data rather than the signal. Using this new definition we get a new set of fitting goals:

$$\begin{aligned} \mathbf{Ns} &\approx \mathbf{Nd} \\ \epsilon \mathbf{DN^{-1}} &\approx \mathbf{0}. \end{aligned} \tag{2}$$

Following Fomel et al. (1997) we can set up the conversion by reformulating it as a preconditioned problem by a simple change of variables ($\mathbf{p} = \mathbf{DN^{-1}}$)

$$\begin{aligned} \mathbf{NND^{-1}p} &\approx \mathbf{Nd} \\ \epsilon \mathbf{p} &\approx \mathbf{0}, \end{aligned} \tag{3}$$

where $\mathbf{p}$ is just a dummy preconditioning variable.

Instead of using patching we followed the methodology of Crawley et al. (1998) and constructed and estimated a space varying filter.

$$\begin{aligned} \mathbf{0} &\approx \mathbf{DA^{-1}p} \\ \mathbf{0} &\approx \mathbf{p} \end{aligned} \tag{4}$$

where $\mathbf{A}$ is a radial smoother (Clapp et al., 1999). For $\mathbf{N}$ we follow a similar procedure assuming an a priori model for the noise.

Synthetic example

At this early stage we decided to show how the method works on a simple synthetic. Figure 1 shows a sea floor with a series of water-bottom multiples. The amplitude of the reflector increases as a function of angle, something that frequency methods have had difficult time handling. The multiple model was constructed by downward continuing (Bevc, 1995) the sea floor reflection, Figure 2. As a result the amplitude information is incorrect, but the kinematics is correct.

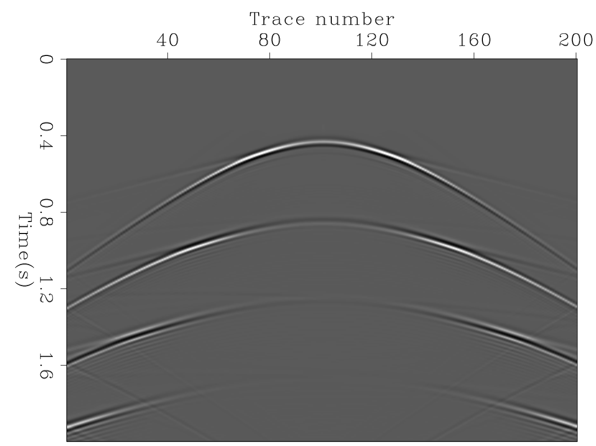

Figure 1: A simple CMP gather with multiples. bob2-bee-cmp [ER]

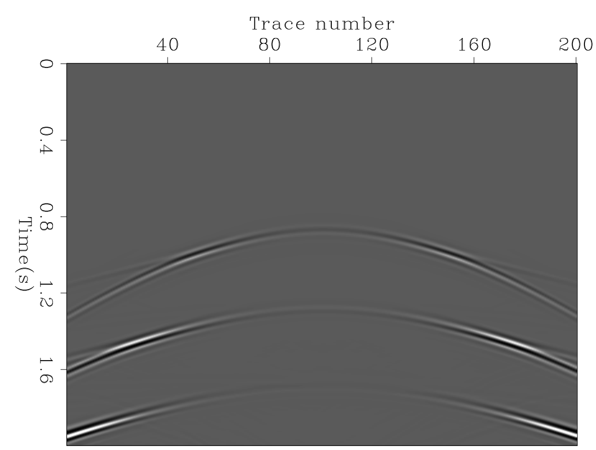

Figure 2: CMP gather in Figure 1 datumed to the surface and back to the seafloor. Note how the amplitude information is wrong but the general kinematics is correct. bob2-bee-mult [ER]

Once we have our data and noise model we estimated a space varying filter for each by applying fitting goal (4). To conserve memory we put a new filter every 15th point in time and third point in offset (Figure 4). These two filters were then used, and fitting goal (3) were applied. Figure 3 shows the result of the separation. We can see some residuals of the filter patches but generally we have done a good job in removing the multiple while preserving the signal.

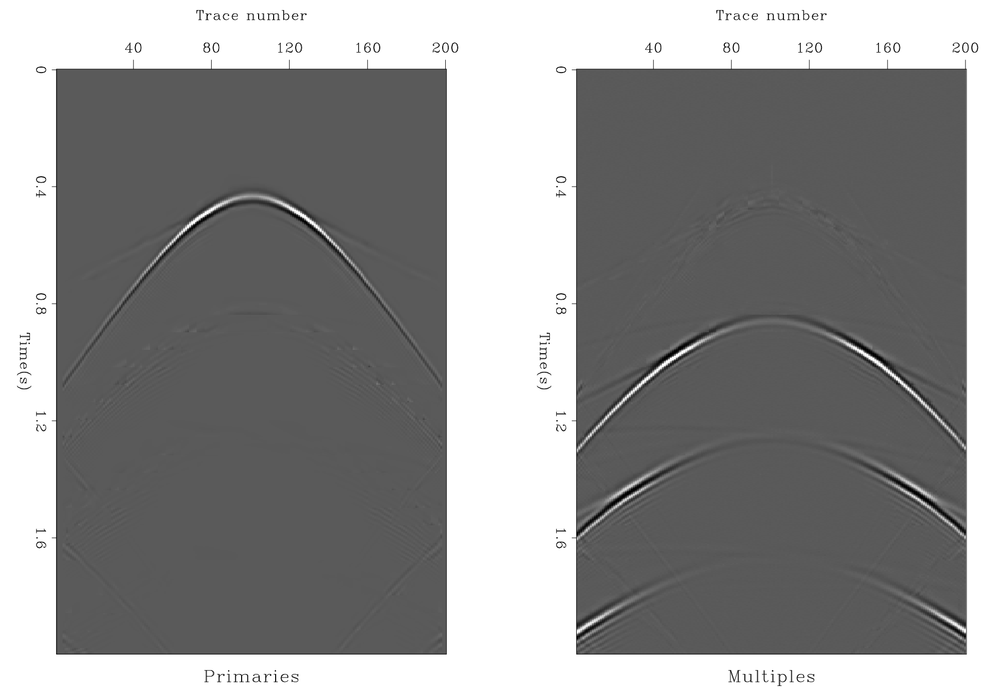

Figure 3: The estimated primaries and mulitpes from Figure 1. bob2-signoi [ER]

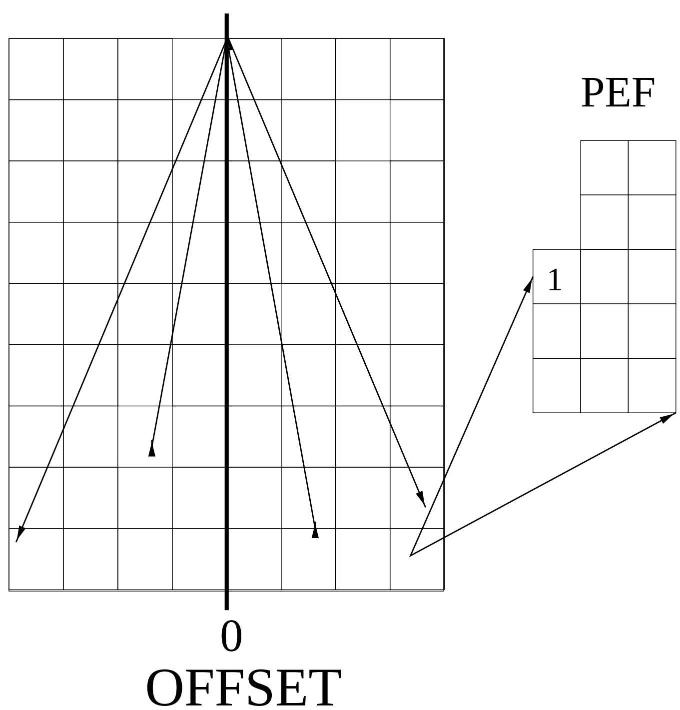

Figure 4: Space varying filter composition. A different filter is placed inside each patch. The filter estimation problem is done globally, with the filter coefficient smoothed in a radial direction. bob2-pef [NR]

Problems

At this preliminary stage there are still some problems to overcome. The separation technique is much more reliant on a stable filter than the interpolation(Crawley, 1999) or feature identification problem(Brown and Clapp, 1999). Some preliminary work on filter stability was done in (Sava and Fomel, 1999; Sava et al., 1998), but the problems associated with non-stationary filters are only beginning to be addressed (Rickett, 1999). To be effective in 3-D, the problem of spatial aliasing has to be dealt with.

HUBER VELOCITY SPACE MULTIPLE ELIMINATION

Transforming seismic data into another domain and then muting is a common multiple suppression technique. The common method is the parabolic radon transform (Foster and Mosher, 1992). This method has the advantage of having a analytic inverse (and is therefore faster), but involves approximating moveouts by parabolas. Lumley et al. (1994) used the more expensive hyperbolic transform and went a step further by forming it as an inversion problem,

$$\mathbf{d} \approx \mathbf{HVm}, \tag{5}$$

where:

d is the CMP gather,

H is a half derivative operator (Prucha, 1999),

V is a velocity transform operator.

They then used an L_2 conjugate gradient algorithm to estimate a (τ, v) model and then muted out the multiples. Unfortunately both methods suffer from multiple and primary energy overlapping.

Huber separation

To get a better (τ, v) model we decided to replace the linear iterative solver used by Lumley et al. (1994) with the Fletcher-Reeves non-linear conjugate gradient conditions (Polak, 1997) and the Dennis-Schnabel line search method (Dennis and Schnabel, 1983). We replaced the L_2 function, with a Huber functional (Huber, 1973) that is less sensitive to large outliers. The Huber functional is L_2 until some cutoff value and then smoothly switches to L_1 (Figure 5). The idea is compromise between the convergence speed of L_2 and the less sensitive nature to outliers with the L_1. Guitton and Symes(1999) showed that the Huber functional does a better job of localizing energy in (t, v) space. For multiples this mean that the primary and multiple trains are better separated.

To show the advantage of the Huber method over a straight L_2 we took a multiple contaminated CMP gather, Figure 6, and iterated on fitting goals (5). Figure 7 shows the envelope of

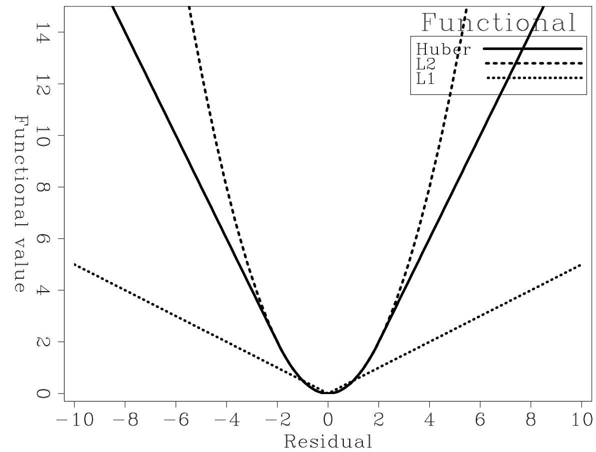

Figure 5: The L_2, Huber, and L_1 functionals. bob2-huber [ER]

the (τ, v) representation of both the Huber and L_2 approach. Note how the Huber result shows a more compact representation of the primary and multiple trains.

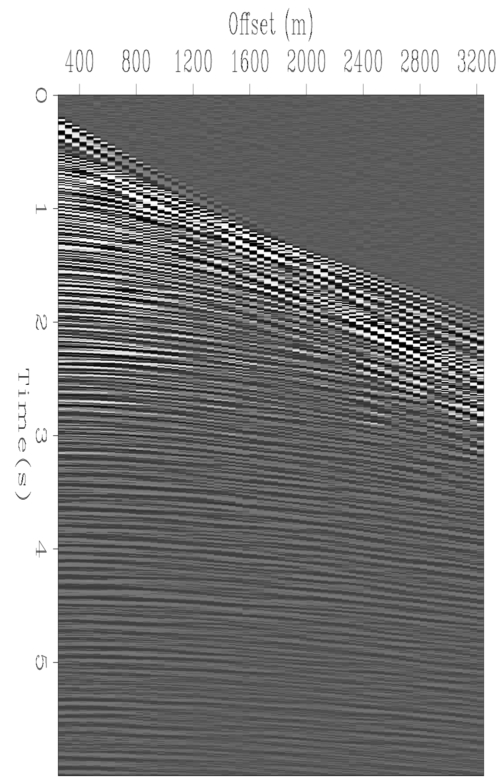

Figure 6: A multiple infested gather from the Mobil AVO dataset. bob2-mobil [ER]

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Figure 7: The envelope of the tau-velocity space representation of the Mobil AVO gather (Figure 6) using both an L_2, left, and a Huber, right, functional. Note how the Huber gather shows more energy and better isolation of the primary train. Further, the L_2 approach show significantly more energy at high, unreasonable, velocities. $\boxed{\text{bob2-compare}}$ [ER]

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