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Removing velocity stack artifacts

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ABSTRACT

The Prediction Error Filter (PEF) is a widely used tool in various geophysical applications such as signal-noise separation and interpolation of missing data. Over the years, SEP has developed tools to estimate non-stationary Prediction Error Filters. Non-stationary PEFs are successfully used for multiple removal, ground-roll attenuation, and in other geophysical problems. I apply a non-stationary PEF to a velocity stack to remove artifacts caused by a limited offset of the data. My first goal is to create an artifact-free model in which individual reflections are easier to identify. To do this I create a simple model of the artifacts in the $\tau - s$ space. This "noise" model is data-independent and relies only on the geometry of the data acquisition and parameters of the velocity stack. Then I estimate a non-stationary PEF on this "noise" model and use it to improve the velocity stack.
In the second part of the paper, I test the possibility of using the described PEF as a preconditioner for a velocity stack least-squares inversion.

INTRODUCTION

To build a velocity stack, we usually construct an operator $\mathbf{H}$ that maps energy from velocity-stack space to offset-travel time space. The adjoint operator $\mathbf{H}'$ maps the energy back to a velocity-stack space. To build the model in a $\tau - s$ domain that is consistent with the data, we then solve the least-squares problem:

$$\mathbf{Hm} - \mathbf{d} \quad \approx \quad \mathbf{0} \tag{1}$$

This problem can be solved using iterative methods. For a simple model the solution is usually obtained in a few iterations. Although this solution may fit the data well, it may have "butterfly" artifacts caused by a limited aperture of the data. To illustrate this, I create a simple model with one spike in the velocity-stack space. Applying the operator $\mathbf{H}$ to this model, I obtain synthetic data set. Then I use this modeled data as an input ($\mathbf{d}$) to solve the least-squares problem (equation 1) for $\mathbf{m}$. Figure 1 shows the original model in the velocity-stack space, the modeled data, the estimated model, and data residual after five iterations of the conjugate gradient method.

As Figure 1 shows, the data residual after five iterations is small but "butterfly" artifacts are clearly present in the solution. It is desirable to obtain a model that has all the energy

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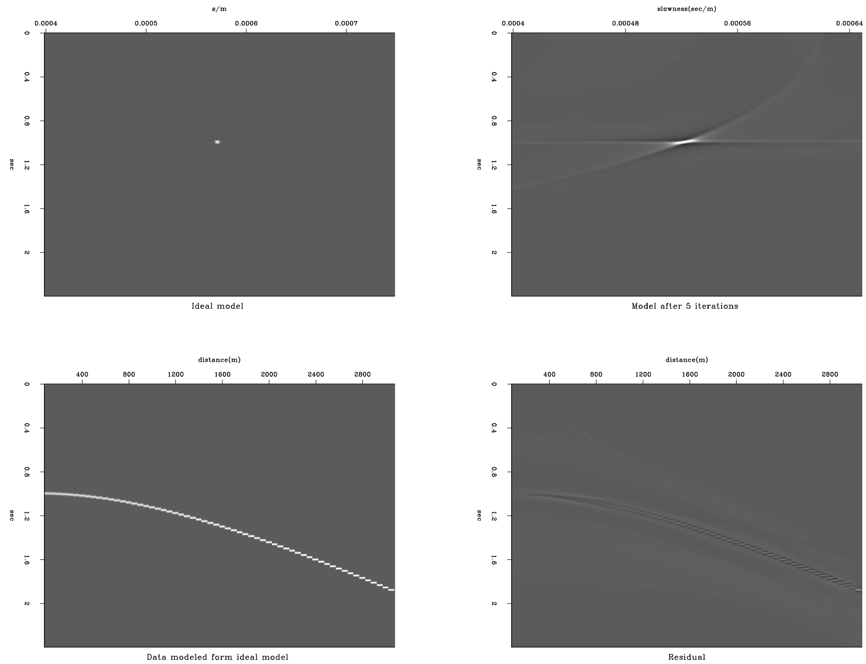

Figure 1: Top left: Ideal model. Top right: Spike after 5 iterations of the conjugate gradient. Bottom left: Data modeled from the ideal model. Botton right: Data residual after 5 iterations andrey-spike [ER]

concentrated at the location of the original spike and fits the data well. This problem has been addressed before. For example, at SEP Nichols (1994) and Guitton (2000) proposed to minimize the L1 norm of the model to create the spiky solution. Sacchi and Ulrych (1995) solved a similar problem using a parabolic Radon trasform, where they solve the problem in a frequency domain. These techniques showed very good results in concentrating the energy of the solution. (They are especially valuable during the multiple attenuation step of the processing.) But for some applications it may be useful to have an inexpensive way to remove artifacts from the model even if the data residual becomes larger. My first goal is to use the spatial predictability of the artifacts to design the operator to remove them. If the technique can make events appear better in a velocity stack panel and is easy to apply, it can be useful in picking velocities and designing masks for a multiple removal. A similar approach may be effective in other geophysical applications where the artifacts have a similar nature; for example, artifacts caused by a limited apperture in Kirchhoff migration.

FILTER DESIGN

To design an operator to remove artifacts from a velocity stack, I am going to use the property of a two-column PEF to destroy a plane wave (Claerbout, 1999). Since artifacts from the far offset have a variable dip; this filter will need to be non-stationary. To design the operator we need to model the artifacts. The model of the artifacts can be created by applying the operator

$\mathbf{H}'$ to the first and the last trace of the data (Figure 2). We should be able to describe such a model with a three-column-wide filter. However, it is easier to divide the model of the artifacts into a “horizontal” and a “vertical” parts. We then create a pair of two-column PEF and train one on the “horizontal” and the other on the “vertical” part of the noise model. These two filters may then be applied to a velocity stack one after another to destroy the artifacts. It is very important to notice that it is not necessary to use traces from real data to model the “noise.” Figure 2 illustrates how these separated parts of the “noise” model will look.

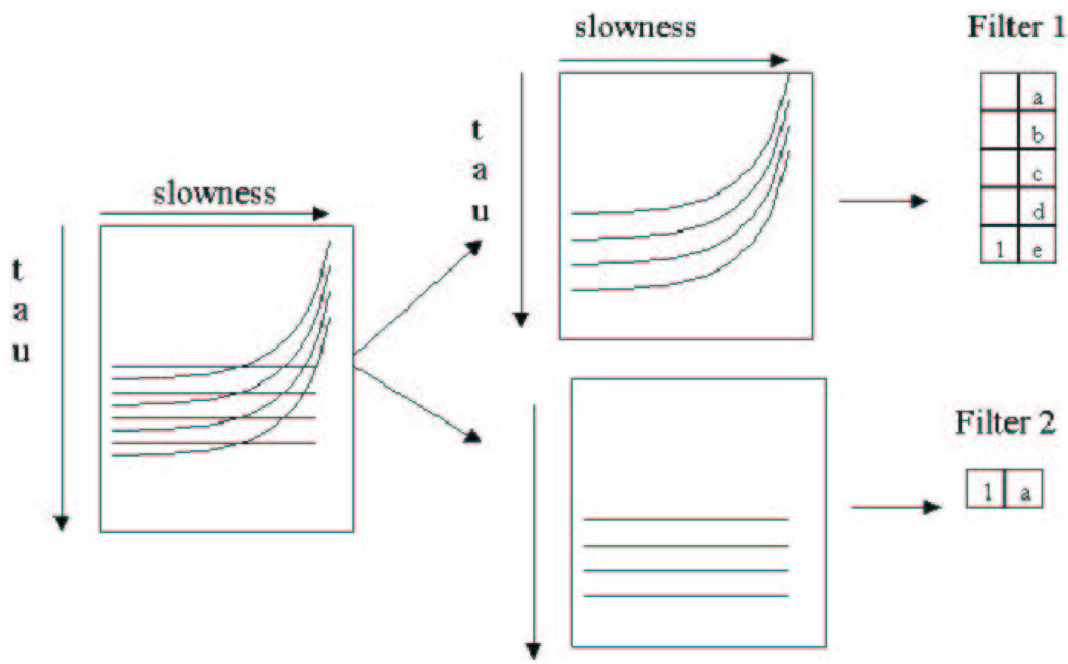

Figure 2: Illustration of different parts of a noise model andrey-noise [NR]

Using this approach, we could create the noise model and PEF only once and then re-use them when needed. This would greatly reduce the cost of the procedure and allow for the design of a stable filter. Designing a stable non-stationary PEF is the most difficult task in any application that uses a non-stationary PEF. However, in this case I have the advantage of being able to compute a non-stationaty PEF before the processing, so I can use various methods of smoothing the filter coefficients. I can also change the “noise” model, which might be important if I try to use this filter in any least-squares inversion schemes later.

APPLICATION OF THE FILTER

In this section I test the approach described in the previous section on a simple synthetic and a real dataset. Figure 3 shows the result of applying this filter to a velocity stack of a synthetic data.

Figure 3 shows that the filter does remove the strongest artifacts and the result spatially looks more like the original spike.

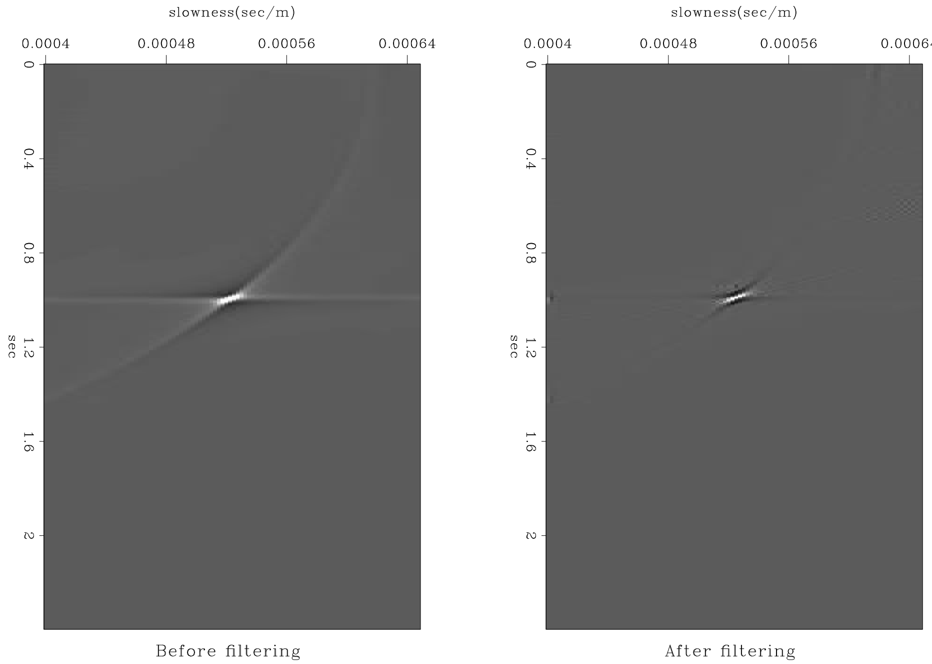

Figure 3: Spike after 5 iterations of conjugate gradient and after removing "butterfly wings." andrey-spike_comp [ER]

Figure 4 shows the result of filtering the velocity stack panel of one CMP gather of the Mobile AVO dataset. As we can see, strong individual events on the right panel are much easier to identify. Water-bottom multiples are clearly separated from other events and easy to identify.

Unfortunately, the filtering removes some of the energy from the model, limiting the application of the simple filtering described above. In the next section I discuss the possibilities and problems of incorporating the filtering approach as described above in a solution of the least-squares problem [equation (1)].

LEAST-SQUARES INVERSION OF A VELOCITY STACK

To make the velocity stack usable for other processing steps such as multiple removal, I should try to incorporate the PEF described above into an inversion scheme that compensates for energy removed during the filtering.

Following the "trial solution" approach described in Claerbout (1999), I change the variables $\mathbf{m} = \mathbf{Pp}$ and solve equation (1) for the preconditioned variable $\mathbf{p}$:

$$\mathbf{HPp} - \mathbf{d} \quad \approx \quad \mathbf{0} \tag{2}$$

Operator $\mathbf{P}$ in equation (2) is a cascade of two filters described in the previous section. After finding a solution for $\mathbf{p}$, I evaluate $\mathbf{m} = \mathbf{Pp}$ to obtain the solution of the original problem.

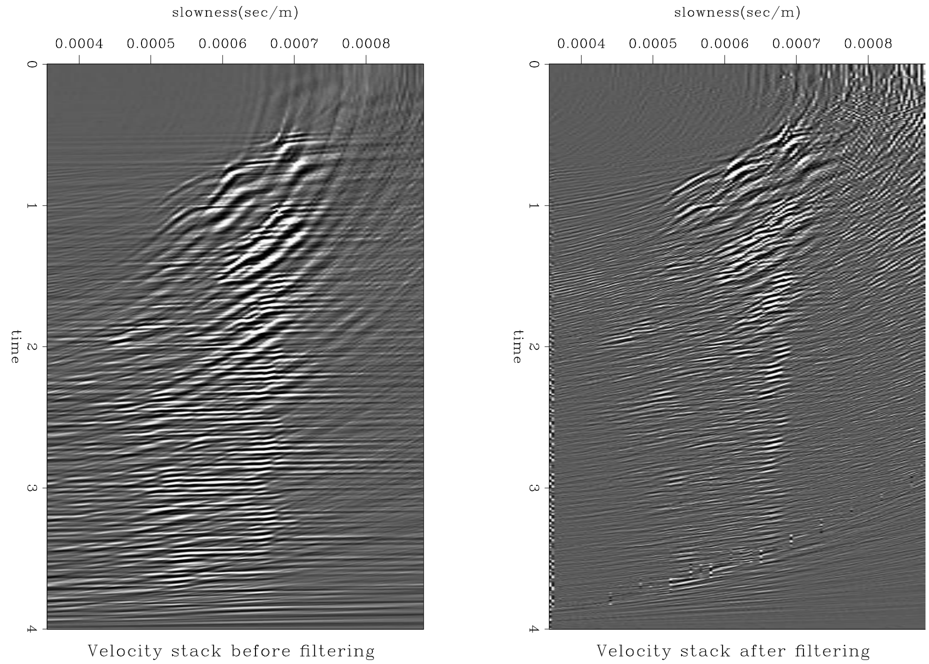

Figure 4: Velocity stack of a CMP from Mobile AVO dataset before and after filtering andrey-mob_comp_500 [ER]

To avoid high frequency noise in the model, I introduce a regularization term into the problem and solve the system of equations:

$$\begin{aligned} \mathbf{HPp} - \mathbf{d} &\approx \mathbf{0} \\ \epsilon \mathbf{Ap} &\approx \mathbf{0} \end{aligned} \tag{3}$$

In this paper I used the laplacian as the regularization operator **A** in equation (3).

Figure 5 shows the solution to the least-squares problem [equation (1)] after 25 iterations of the conjugate-gradient method, the velocity stack after the filtering, and the solution to the preconditioned least-squares problem [equation (3)] after 25 iterations of the conjugate-gradient.

Figure 6 shows the residual for the preconditioned problem [equation (3)] and the problem without preconditioning [equation (1)].

As Figures 5 and 6 show, although the solution for the preconditioned problem does not have artifacts, it converges much slower than the solution to the problem without preconditioning, which probably makes this method of preconditioning impractical.

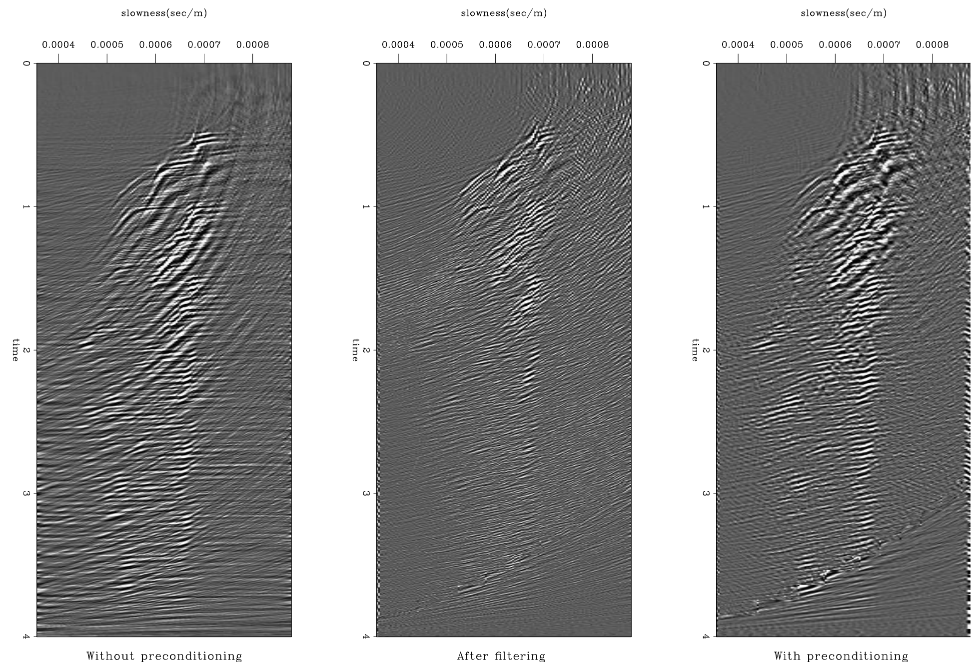

Figure 5: Left: Velocity stack after 25 iterations without preconditioning. Center: Velocity stack after filtering. Right: Velocity stack after 25 iterations with preconditioning. andrey-prec [ER]

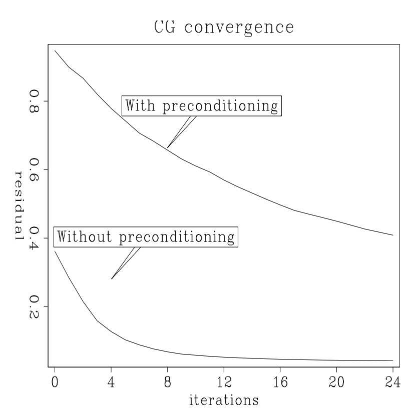

Figure 6: CG convergence with and without preconditioning andrey-res_ann [ER]

CONCLUSIONS

I have presented a method to remove velocity stack artifacts caused by the limited offset of the acquisitions geometry. This method uses a non-stationary PEF and is computationally inexpensive and data independent. Tests on the data show that this approach successfully removes artifacts from a velocity stack. This method may be helpful in velocity analysis and other applications where artifacts are easy to model.

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