Statics preserving projection filtering

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Summary

Projection filtering has been used for many years in seismic processing as a tool to extract a meaningful signal out of noisy data. We show that its effectiveness reaches a limit when seismic events are affected by static shifts. Such shifts degrade the lateral coherency of the data, which is the strongest hypothesis required by projection filtering. We propose a method to estimate projection filters and static shifts simultaneously in order to perform noise attenuation in the presence of static shifts in the data. We then show results on synthetic and real data to demonstrate denoising capabilities of our algorithm.

Introduction

Random noise attenuation has been a subject of interest for many years in seismic processing. We now have a wide variety of tools to perform such a task. From prediction and projection filtering (Canales, 1984; Soubaras, 1995) to coherency enhancement (Gulunay, 2007; Traonmilin et al., 2008), we can efficiently address many situations where random noise contaminates the data. However, in all of these methods, we have to rely on the hypothesis that the signal is spatially coherent in order to estimate the signal.

In some cases, this assumption is hardly met. In land data, static shifts caused by near surface propagation effects harm the lateral coherency of seismic events. With wide-azimuth acquisitions, azimuthal anisotropy as well as structural dip also generates shifts in the pre-stack domain, leading to a rather difficult velocity analysis and more generally, pre-stack processing. In these situations, we face the following problem: if we cannot correct for these shifts, we cannot use conventional noise attenuation techniques that rely on lateral coherency and inversely if we cannot attenuate noise, it will be difficult to estimate the shifts. Usual workarounds lead to tedious workflows of denoising and picking iterations (surface consistent refraction statics picking and calculation, velocity picking…).

In this paper, we propose a method which estimates static shifts and projection filters at the same time, allowing for the attenuation of random noise when seismic events are affected by large magnitude static shifts. After a theoretical description of our algorithm, we show its application on synthetic and real data for various processing steps.

Theory

Let us write the problem of estimating static shifts and a prediction error filter at the same time:

$$\text{find argmin}_{A,S} \|ASd\|^2 \quad (1)$$

where A is the prediction error filtering matrix, S is the inverse static shift matrix (representing the application of one static shift per trace), d is the data in the f-x domain. If we can calculate A and S, we will then derive a projection error filter P from A (Soubaras, 1995) and use it to obtain a better estimate of the noise ε contaminating the data:

$$\varepsilon = S^{-1}PSd \quad (2)$$

We immediately see that the relation between unknown and known parameters in equation 1 is nonlinear (bilinear), so we cannot hope to solve this problem with a simple linear least squares technique. We therefore need to use a non linear method to solve this problem.

The most straightforward way to perform a nonlinear minimization is to use an iterative scheme where we linearize locally the problem. Let us assume that we have an estimate of the shifts S_i, and that lateral coherency is enhanced in the data when this estimate is applied. Fixing S_i in the minimization will allow us to get an estimate of the prediction error filter A_{i+1}:

$$\text{find argmin}_{A_{i+1}} \|A_{i+1}\, S_i d\|^2 \quad (3)$$

We derive the projection error filter P_{i+1} corresponding to A_{i+1} and use it to solve the following problem for S_{i+1}:

$$\text{argmin}_{S_{i+1}} \|P_{i+1}S_{i+1}d\|^2 = \text{argmin}_{S_{i+1}}\, \varepsilon_i \quad (4)$$

where S_{i+1} is a static shifts operator. With real data, we have little guarantee that solving this system directly will give correct shifts because coherent noise can bias the solution. There is as well a possibility that we fall in a local minimum. Instead, we use a conjugate gradient update for S_{i+1}:

$$S_{i+1} = S_i - \mu_i \overline{\nabla}_S\, \varepsilon_i \quad (5)$$

where $\overline{\nabla}_S\, \varepsilon_i$ is the conjugate gradient direction and μ_i is the step size.

With this update method, we can control the values taken by S_{i+1} and have the guarantee that our objective function (Eq 4) will be decreased.

Equation 3 and 5 define our iterative minimization algorithm. We only need to define the initialization values of this algorithm and the step size:

- In practice, we start our algorithm with S_0=*Identity* (initial shifts set to 0). This is justified by the fact that we rarely encounter cases where coherency is totally destroyed by shifts.
- To set up the step size, we have the possibility to perform a line search or to find a heuristic method to set it appropriately. We used the latter one for computational complexity consideration. We also used the step size to limit the solution space of the statics term in the objective function and to converge towards the desired result.

As this problem is nonlinear, local minima can be present in the objective function. We found out that these local minima are mostly due to aliasing caused by static shifts. We used the following technique to deal with aliasing: we start iterations with low frequencies, and bring more frequencies in the objective function as iterations go. With this method, we were able to estimate shifts having values as large as the inverse of the minimum frequency present in the data.

Synthetic data examples

We generated two synthetic datasets fitting the data model used in our algorithm. It consists of three band limited linear events, with random static shifts applied and random noise added. Two different magnitudes of shifts were tested. In Figure 1, the shifts values are randomly distributed between - 4ms and +4ms, which is the sampling interval. In Figure 2, the shifts are randomly distributed between -32ms and +32ms (with a sampling interval of 4ms). We see (Figure 1) that we were able to remove random noise and to preserve the shifts at the same time, even when shifts are large (Figure 2). We also show in these figures the limit of conventional projection filtering: irregularities are smeared and primary events are harmed, most particularly when shifts in the data are large.

Our second synthetic dataset (Figure 3) simulates an event in a wide-azimuth CMP gather corrected with normal move-out. We see that azimuthal anisotropy caused by structural dip generates some jitters on the event. They were handled well by our algorithm, even as the magnitude of shifts increases at large offsets. The accuracy of the filtering is particularly noticeable on the side lobes of the wavelet which were perfectly preserved. This example highlights the fact that our algorithm is efficient even when the amplitude of the shifts is highly variable.

Real data examples

In Figure 4, we use our technique to enhance the flattening workflow of land wide-azimuth common image gathers (CIGs) (Gulunay et al., 2007). The large amount of noise in the pre-stack data (Figure 4a) leads to a difficult application of this process: as the flattening method is mostly a local process, it will have a problem dealing with areas were the signal is completely overpowered by noise. We consequently observe that the flattening of the noisy data does not lead to an optimal focusing of the stack (Figure 4c). After the application of statics preserving projection filtering, the signal to noise ratio of the CIGs is improved and static shifts are preserved (Figure 4b). Because statics preserving projection filtering uses bigger windows, we were able to recover the signal even in areas were it is very weak with respect to noise. We used these cleaned CIGs for the calculation of time shifts in the flattening process. We applied the newly calculated shifts to the initial noisy gathers, and stacked the result (Figure 4d). The higher signal to noise ratio on cleaned gathers led to a better estimation of time shifts for flattening, which results in a better focusing of the stack, especially where events are dipping.

Another application of statics preserving projection filtering can be the cleaning of refracted arrivals that are used for the derivation of statics for reflection data. In Figure 5, we show that we were able to attenuate the noise contaminating a gather containing linearly moved out refractors while preserving statics information for an eventual picking.

Conclusion

With statics preserving projection filtering, we are now able to attenuate random noise when large magnitude static shifts are present in the data. We also demonstrated that our method brings out a significant uplift in signal to noise ratio when processing wide-azimuth land data.

Acknowledgments

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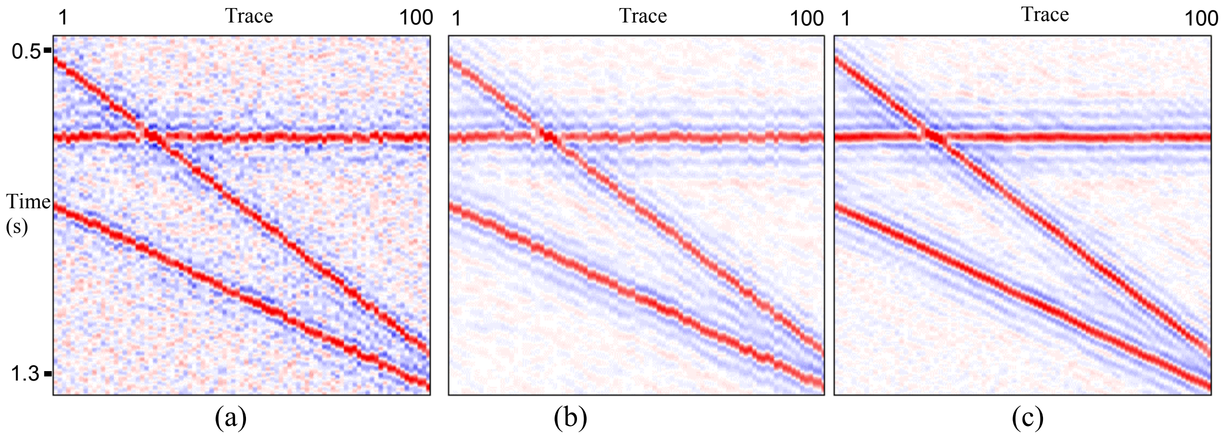

Figure 1: Denoising of 3 linear events with small random shifts (a) input, (b) statics preserving projection filtering, (c) conventional projection filtering.

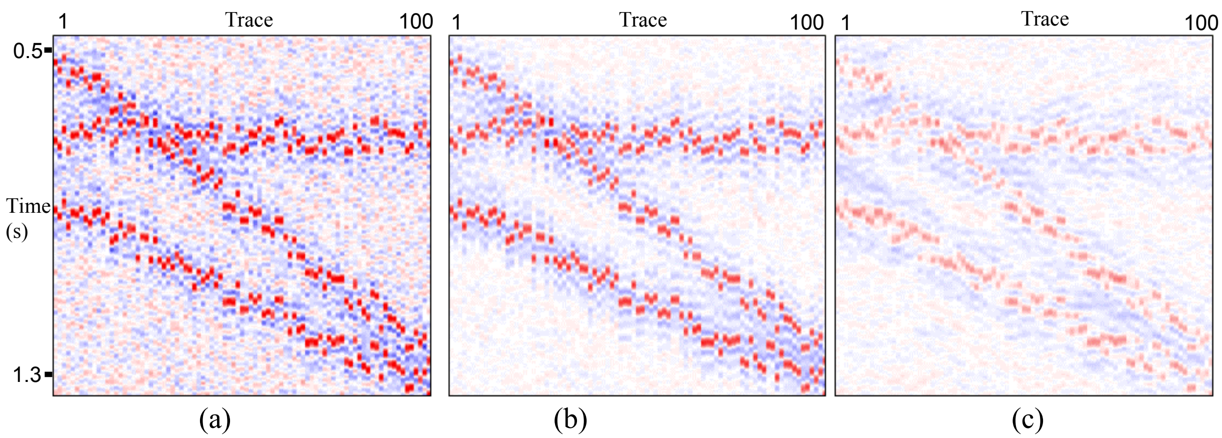

Figure 2: Denoising of 3 linear events with large random shifts (a) input, (b) statics preserving projection filtering, (c) conventional projection filtering

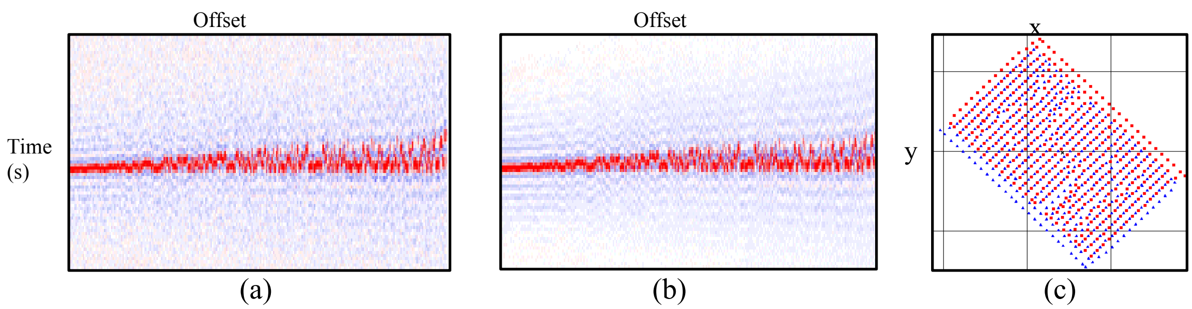

Figure 3: Denoising of a synthetic event in a wide-azimuth CMP corrected with NMO only (a) input (b) statics preserving projection filtering (c) Source (blue) – Receiver (red) map of the CMP.

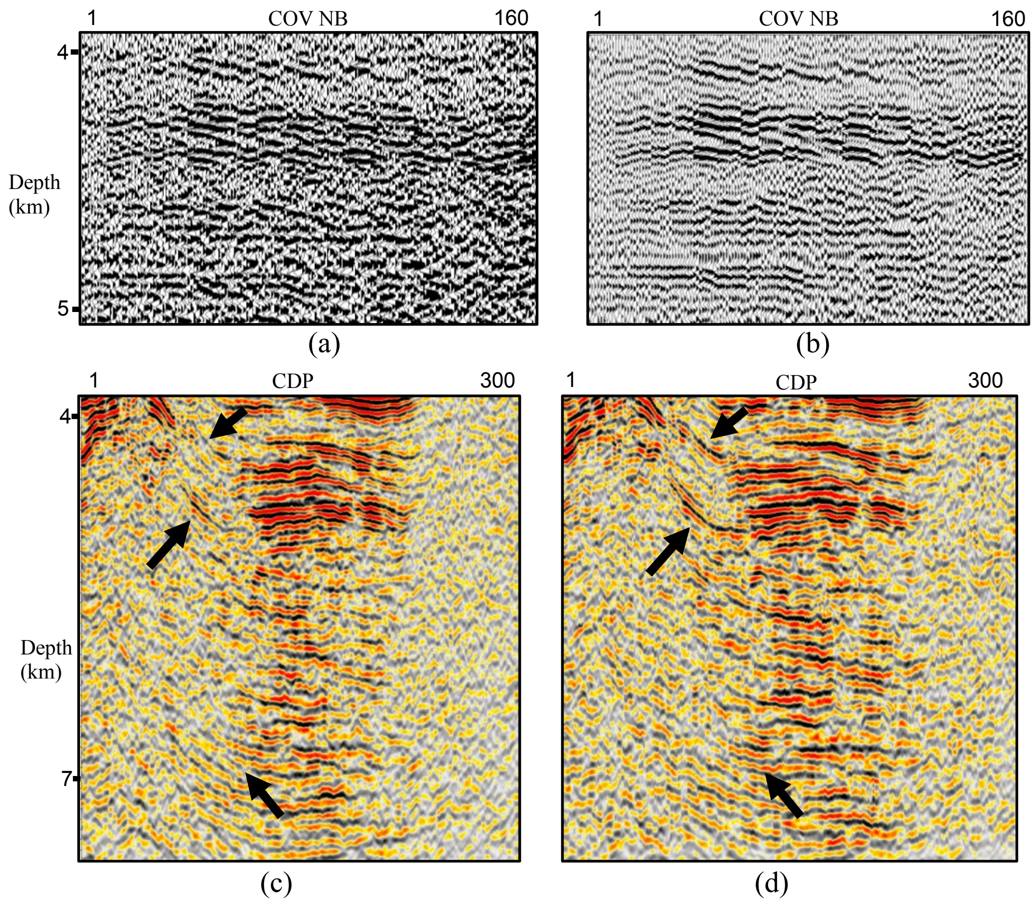

Figure 4: Denoising of wide-azimuth CIGs and application (a) a raw CIG, (b) the result of statics preserving projection filtering (c) stack of flattened noisy gathers (d) stack of flattened noisy gathers using time shifts calculated on gathers denoised with statics preserving projection filtering.

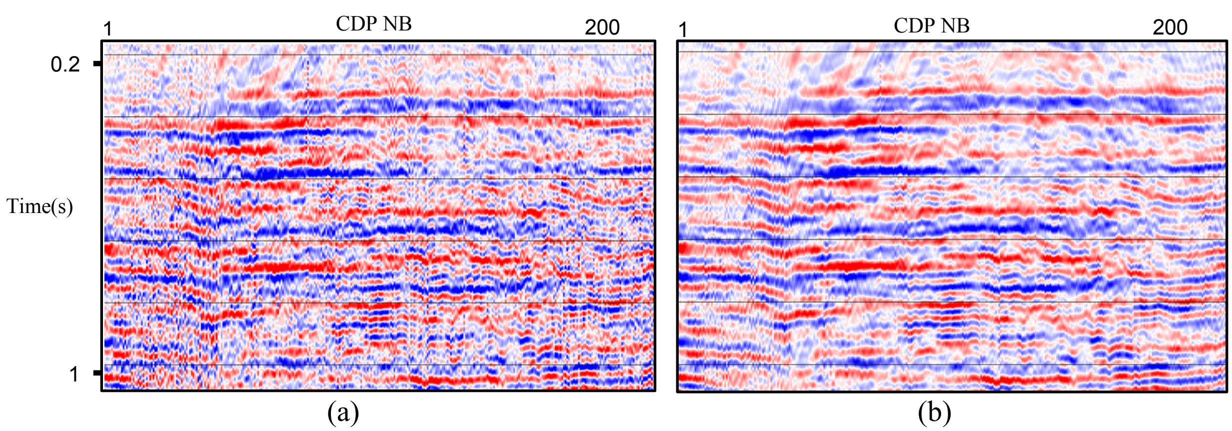

Figure 5: Denoising of first breaks (a) input (b) after statics preserving projection filtering applied.

EDITED REFERENCES
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REFERENCES

Canales, L. L., 1984, Random noise reduction: SEG, Expanded Abstracts, **3**, 525–527, doi:10.1190/1.1894168.

Gulunay, N., J. Holden, and J. Connor, 2007, Coherency enhancement on 3D seismic data by dip detection and dip selection: SEG, Expanded Abstracts, **26**, 2625–2629, doi:10.1190/1.27.

Gulunay, N., M. Magesan, and H. H. Roende, 2007, Gather flattening: The Leading Edge, **26**, 1538–1543, doi:10.1190/1.2821939.

Soubaras, R., 1995, Prestack random and impulsive noise attenuation by *f-x* projection filtering: SEG, Expanded Abstracts, **14**, 711–714, doi:10.1190/1.1887383.

Traonmilin, Y., and P. Herrmann, 2008, Structurally consistent *f-x* filtering: SEG Expanded Abstracts, **27**, 2642–2646, doi:10.1190/1.3063891.