Structure-oriented Filter by Domain Decomposition

Marcos Machado (Petrobras), Carlos Cunha* (Petrobras)

This paper was prepared for presentation during the 14th International Congress of the Brazilian Geophysical Society held in Rio de Janeiro, Brazil, August 3-6, 2015.

Abstract

Filtering is a general term for the process of decomposing the input data into a complete set of components and selecting a limited part of these components for the output. It is often used to separate noise from signal, whenever signal and noise have distinct distributions among the set of components. The drawback in such cases is the absence of some components of the original data in the filtered data. We introduce a filter process that preserves the full set of components in the output data. First, the data is decomposed in two components: one dominated by noise and the other dominated by signal. Structure-oriented Smoothing is applied to the noise-dominant part, guided by the signal-dominant part. The smoothed noise component is then combined with the signal component to generate the filtered full-component data. Examples with field data show the advantages of this strategy, as well as its flexibility for several other applications.

Introduction

A large variety of filters are routinely used in seismic data processing in order to improve its signal-to-noise ratio. It is also common practice to apply filters to better pre-condition data, prior to seismic inversion algorithms such as deconvolution, elastic inversion, and FWI.

The Structure-oriented Filter (Fehmers and Höcker, 2003) belongs to a class of low-pass spatial filter that performs smoothing along the structures present in the data, enhancing them, while preserving the main discontinuities, such as faults and channels. The filter is based on 2 concepts:

1. The data structure orientation is estimated by the Gradient Structure Tensor (GST) (Vliet et al., 1995);
2. The oriented smoothing of the input data is obtained by the application of the Anisotropic Diffusion Equation (Weickert, 1997) or a similar differential equation (Hale, 2009).

The anisotropy is encoded by the Diffusion Tensor, which is obtained from the GST. Also, a factor is applied on the Diffusion Tensor to decrease the smoothing around the data discontinuities.

A side effect of this strategy to preserve discontinuities is that in regions where the noise is sufficiently strong, the structure orientation will not be well resolved, leading the filter to stop. In such cases the noise is not attenuated.

Another class of filters, called Frequency Slice Filtering (Hodgson et al., 2002; Whitcombe et al., 2007), changes the domain of the 3D data from X-Y-Time to X-Y-Frequency by a 1D FFT. In this new domain, separate filters can be applied to each 2D constant frequency slice. In case of noise specific to a particular frequency range, this strategy permits to use a smoothing filter, for example, median filter, on that frequency range, without affecting the rest of the data. The filter size is appropriate to each frequency to avoid harming the imaging. Once filtered, the resultant data are transformed back to the original X-Y-Time domain.

A variation of this approach uses 1D Wavelet Transform to split data into several scales (Whitcombe, 2008). In that proposal, a kind of structure-oriented filter is applied to each scale, avoiding problems with steep dips. But, again, in presence of strong noise or aliasing, the signal orientation is lost or incorrect.

To overcome this limitation we first observe that the Structure-oriented Filter has 2 independent steps: the Diffusion Tensor building (the building step) and the Diffusion equation numeric solution (application step). Therefore, the Diffusion Tensor can be built from one input data and the resultant Diffusion equation can be applied on another input data.

To create the two different data we use the concept of domain decomposition. Seismic data can be decomposed by a variety of operators, depending on the particular attribute of the data one wishes to explore. Some noises have a specific dip orientation and can be filtered out in the F-K or Radon domain, while others are more dominant in a particular range of frequency and can be attenuated with a band-pass filter. Selecting just a particular range of data components - where signal dominates noise - improves the overall signal to noise ratio at the expense of losing relevant information associated with the discarded components.

Our approach to filtering is based on three premises:

- Signal-to-noise ratio varies along the different components of a particular domain decomposition of the data.
- The dominant geometric features of the data do not change significantly for different components of that same data decomposition.
- Signal and noise have distinct local geometries.

Whenever these premises are satisfied, it is possible to attenuate the noise in the components where it is dominant, without doing much harm to the signal associated with the same components.

Instead of selecting some components and discarding others, we use the signal-dominant components to estimate the signal geometry and attenuate the noise in the noise-dominant components by structure-oriented smoothing of the misaligned noise.

This paper is organized as follows. First, we discuss the process of Filtering by Domain Decomposition. Then, we show some results using this process, in particular, decomposing the data in the frequency domain and applying the Structure-oriented Smoothing filter to the target components. Finally, we present the conclusions.

Method

In this paper, we introduce the concept of Filtering by Domain Decomposition (FDD). Filters based on this concept are performed in 4 steps:

1. Decomposition: First, we change the data from X-Y-Time domain to another one, where the data could be decomposed in 2 (or more) complementary components, such that, at least one of them is (almost) noise free, while, in the other components, the noise is apparent. We call the 2 sets of components as the driver and the target components.
2. Smoothing Filter Building: From the driver component, we compute a smoothing filter. Observe that, now, the noise has no influence over the filter computation. Only the features present on the driver component are used to compute the smoothing filter.
3. Target Smoothing: We apply the smoothing filter over the target components. Observe that we do not simply discard the noise component; we attenuate its noise and preserve its signal content.
4. Recomposition: Finally, we recombine the smoothed target with the driver component, obtaining the resultant filtered data in the original X-Y-Time domain.

These four steps are summarized by Figure 1.

The abstract FDD concept can be realized in many concrete ways, depending on the choice of the decomposition strategy and of the smoothing filter. In particular, the Structure-oriented Filter is very suited to be used in FDD, due its 2 steps independence, as commented before.

One of the important features of this approach is that the filtered data shows the same stratigraphic characteristics of the original data, since it preserves their full bandwidth.

The characteristics of the decomposition operator can vary in time and space. For instance a time dependent (horizon controlled) band-pass filter can be applied to the original data, to produce the driver component. The target component would be just the difference between the original data and the driver component. The recomposition is achieved by summing the driver component to the filtered target component.

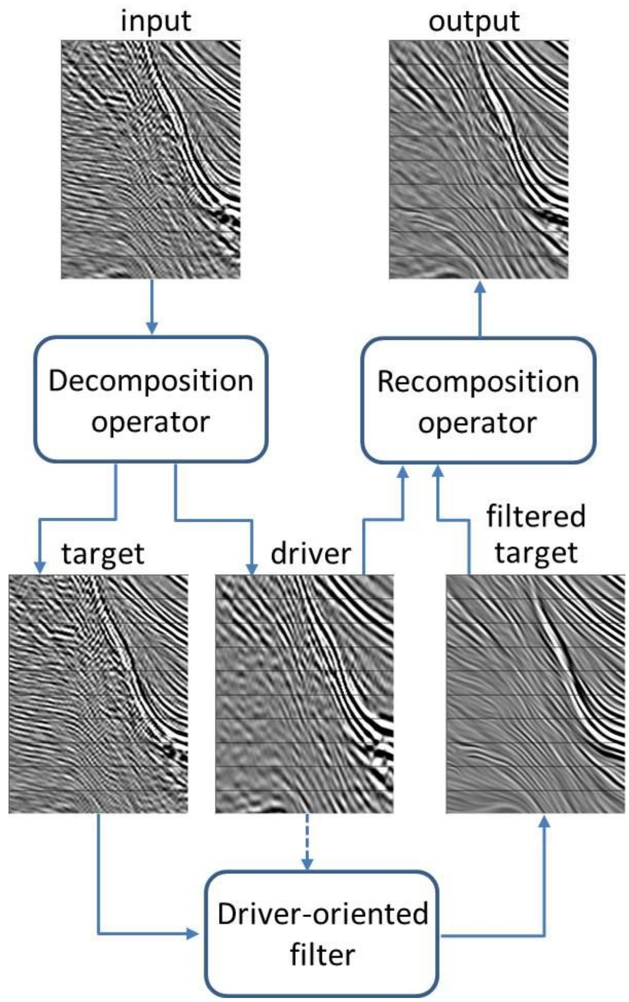

Figure 1 – Diagram illustrating the domain decomposition filtering process. In this particular case the decomposition operator is a band-pass filter. Notice the removal of the spatial aliasing and the removal of the internal multiples in the bottom right and top right images.

This procedure can be generalized to decomposing the data d in a set of k components d_i, as expressed by Equation (1):

$$d = d_{1,k} = \sum_{i=1}^{i=k} d_i \tag{1}$$

We define the operator $H(g)$ as the structural smoothing filter guided by data g. Recomposition of the full bandwidth by successive filtering of each component is achieved by the following recursion:

$$g_{1,i} = g_{1,i-1} + H(g_{1,i-1})\, d_i$$

(2)

$$g_{1,1} = d_1$$

where the component d_1 is the initial driver component and the resulting data is $g_{1,k}$ (the end of the recursion).

This successive bandwidth expansion approach is particularly important to avoid spatial aliasing and loss of resolution during the process.

Examples

We illustrate the application of FDD with three examples of band-pass filtering for noises with different characteristics.

The first example refers to a pre-salt interval in the Santos basin in which internal multiple reflections interfere with non-conform primary interfaces generating chaotic patterns with conflicting dips (Figure 2-a)). Due to the differences in their propagation paths, the internal multiples have a higher dominant frequency than the primary events. This difference becomes clear when we compare Figures 2-c) and 2-d), the former being the original data filtered with a 5-10-20-25 Hz band-pass and the latter the difference between the original data and its band-passed version. Applying the Structure-oriented Smoothing on the target data (Figure 2-c)), guided by the driver data (2-d)), attenuates some of the multiple-related events. Summing back the band-limited component (2-d)) to the smoothed version of 2-c)) leads to the output data displayed in Figure 2-b)). Although multiple-related noise is still present in the data after FDD has been applied, the result is cleaner, easier to interpret, and better conditioned for computation of attributes, while still keeping the same frequency content of the original data.

In Figure 3-a), we show the result obtained with the standard Structure-oriented Filter (structure identification and smoothing using the same original data). For comparison purpose, in Figure 3-b), we show again the image generated with FDD. The parameter set used is the same in both cases. We can see that the FDD result shows a less artificial appearance when compared with the standard filter. Also, in Figure 3-a) the artifacts originated from the multiples are enhanced in some places, while they are attenuated in Figure 3-b).

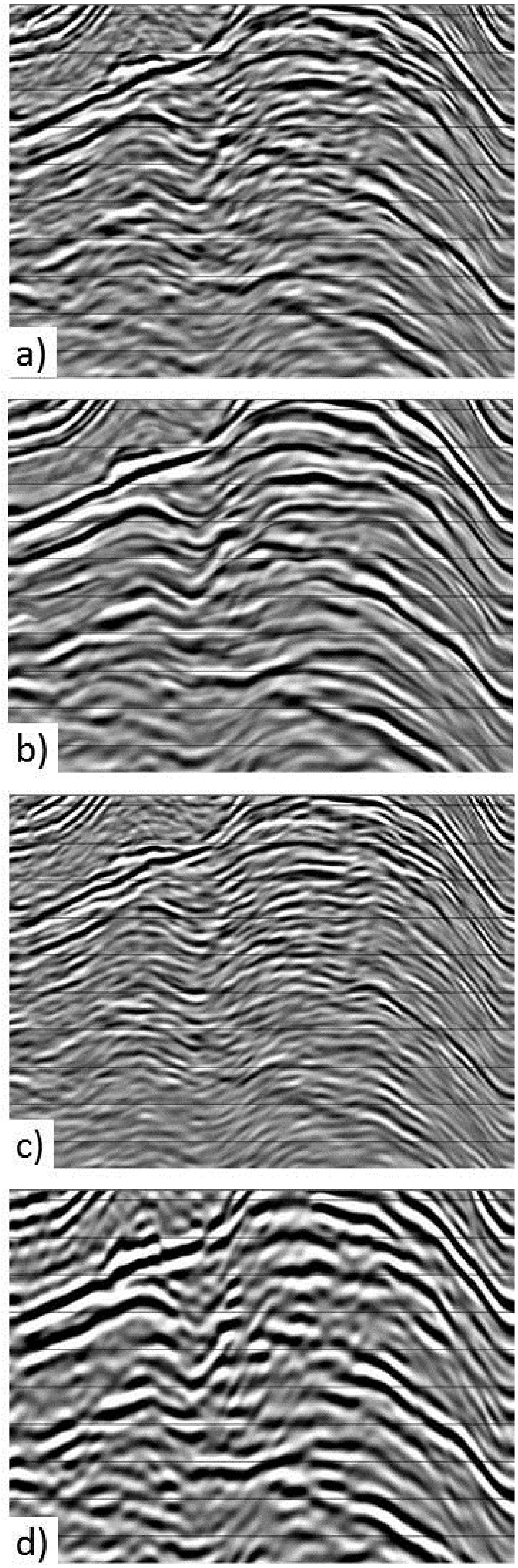

Figure 2 – a) Original data with conflicting dips events, and b) after application of FDD. c) Target component = a-d, where conflicting dips became more apparent. d) Driver component = 5-10-20-25 Hz band-pass filter of a.

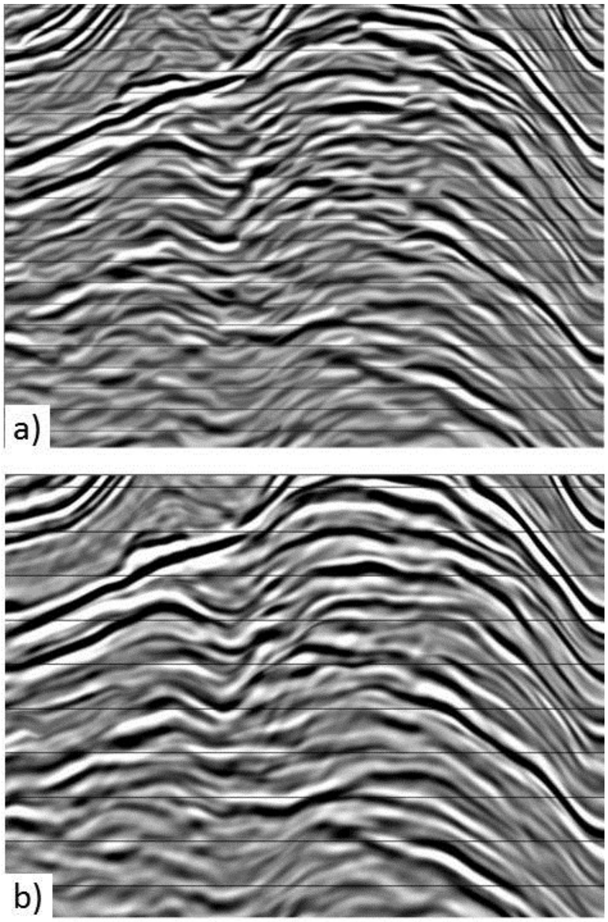

Figure 3 - a) result of the direct application of the Structure-oriented Filter; b) result of FDD (same as Figure 2-a)).

In the second example, the FDD is used to remove low-frequency migration noise in the Albian carbonate interval of a Campos basin data, as shown in Figure 4-a). This low-frequency noise is caused by a combination of the strong impedance contrast at the base of the Albian with irregularities in the acquisition geometry not resolved during the data regularization step. To guide the FDD process we chose to apply a high-pass filter to the original data as shows Figure 4-d). Subtracting the high-passed data from the original data generates the target (Figure 4-c).

Comparison between Figures 4-c) and 4-d) shows that the noise is dominant in 4-c) and absent in 4-d). Driver-oriented smoothing of the target component recomposed with the driver component leads to the result displayed in Figure 4-b).

It is important to notice that although the low-frequency noise is absent from the data after the FDD process, semi vertical faults and carbonate mound flanks with the same frequency content as the removed noise remain preserved. This is possible because the high-frequency driver (Figure 4-d) contains the lateral discontinuities associated to such events.

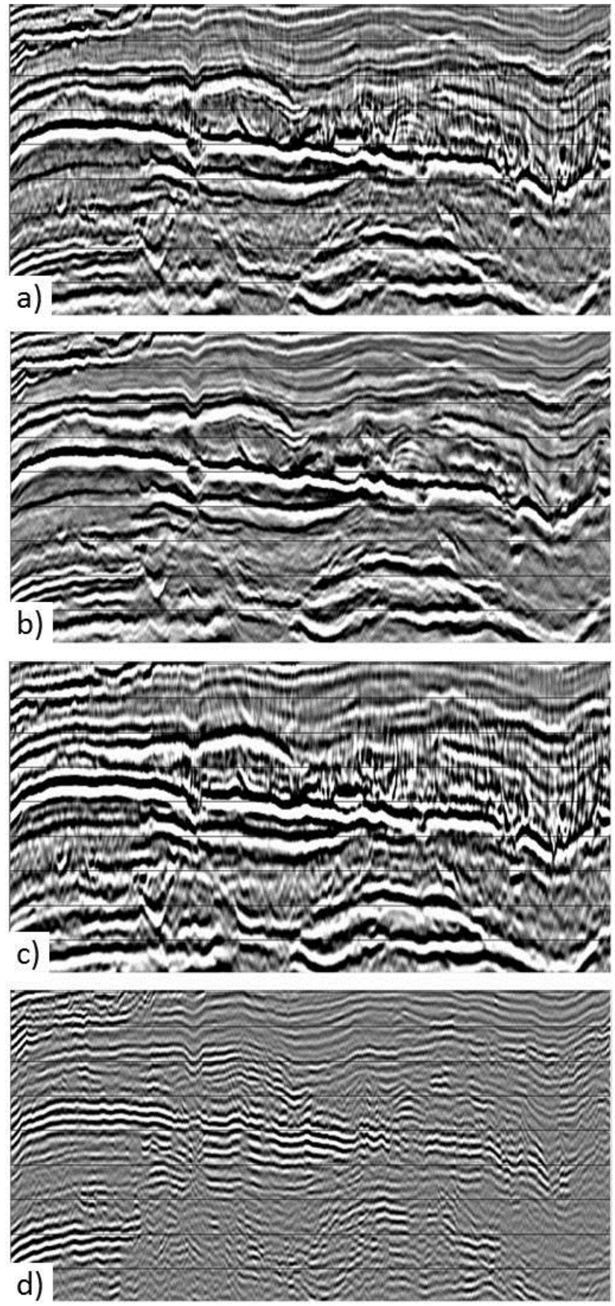

Figure 4 – a) Original data with low-frequency migration artefacts, and b) after application of FDD. c) Target component = (a) - (d). d) Driver component = 30-out Hz band-pass filter of (a).

Figure 5 shows the amplitude spectra for the original data, the data after the band-pass filter, and the data after application of FDD, for the two previous examples. The spectra for the first example (Figure 5-a)) demonstrates that, differently from the band-pass filter, the FDD preserves the useful bandwidth of the original data. There are two possible explanations for the attenuation observed above 25 Hz. In this specific case, we know that the signal in the original data is already relatively week at high frequencies due to absorption effects, so the attenuation is only related to the noise. Another possibility is that the data contain subtle stratigraphic features that are prone to distortion due to side-lobe interference at the low-frequency band of the driver data. In such cases, these features could be attenuated by FDD. If so, it is recommended to use the recursion defined in Equation (2).

For the second example (Figure 5-b)) the full spectrum is recovered without attenuation.

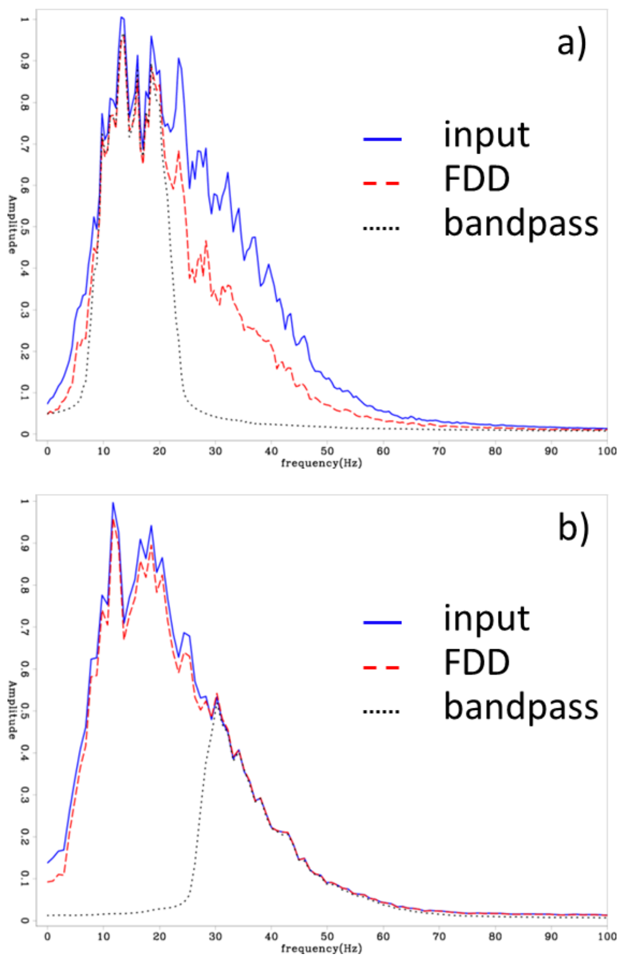

Figure 5 – Amplitude spectra for the original data, the data after band-pass, and the data after FDD for: a) the first example (Figure 2), and b) the second example (Figure 4).

The third example shows the improvements achieved by using FDD as a data pre-conditioner for a reflectivity inversion technique applied to an upper Cretaceous interval from Santos basin. A band-pass filter is usually applied prior the inversion to prevent the amplification of high frequency noise during the process. Figure 6-a) shows the data after the application of a 0-5-40-45 Hz band-pass filter, while 6-b) shows the same data after application of FDD, using the previous band-pass data as the driver. Figure 6-c) and 6-d) show, respectively, the results of the reflectivity inversion using the band-pass data and the FDD data as input. Although we can hardly notice the difference between the two input data (Figures 6-a), and 6-b)), the result of the FDD conditioned inversion is much less contaminated by noise than the band-pass conditioned result.

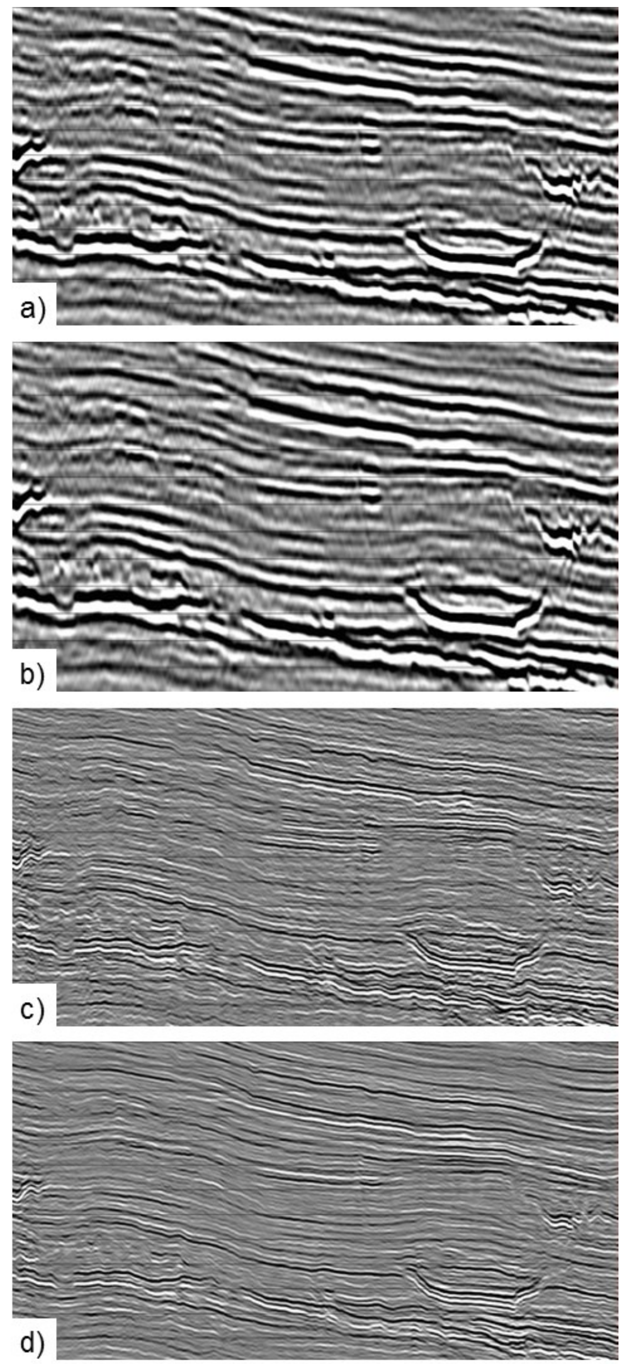

Figure 6 – Data after application of a) 0-5-40-45 Hz band-pass; b) FDD using this band-pass as a guide; c) reflectivity inversion of the band-pass data; d) reflectivity inversion of the FDD data.

Conclusions

In this paper we presented a new filter strategy, the Filter by Domain Decomposition. This involves a change from the original domain to another one where the data can be decomposed in a noise-free component, the driver, and one or more components where the noise is present, the target components. Then, it prescribes a filter whose construction is guided by the driver component and is applied to the target(s) component(s). The Structure-oriented Filter fits well for this purpose. There are two advantages in this strategy: the structure of the filter is less affected by the noise that it is designed to attenuate and the amplitude spectrum of the filtered data is reasonably well preserved. As a result, the output data show a less artificial appearance when compared to those obtained with the standard Structure-oriented Filter directly applied to the data.

Other potential domain decomposition for the application of this strategy involves the use of the offset or the azimuth dimensions to define different components. Data are usually less noisy in some offset/azimuth ranges, which can be used as drivers to design filters to be applied to the other components.

Acknowledgments

We thank Petrobras for permission to publish this work. We also thank Juliana Alencar Antunes, Milena de Lima Frej and Danilo de Oliveira Domingos for helpful discussions and support on data processing.

References

Fehmers, G. C., and C. F. W. Hocker, 2003, Fast structural interpretation with structure-oriented filtering: Geophysics, 68, 1286–1293.

Hale, D., 2009. Structure-oriented smoothing and semblance. CWP Report 635, 261–270.

Hodgson, L., D. Whitcombe, S. Lancaster, and P. Lecocq, 2002, Frequency slice filtering—A novel method of seismic noise attenuation: Presented at the 72nd Annual International Meeting, SEG.

Vliet, Lucas J. Van, & Verbeek, Piet W. 1995. Estimators for Orientation and Anisotropy in Digitized Images. Pages 442–450 of: ASCI95, Proc. First Annual Conference of the Advanced School for Computing and Imaging (Heijen, NL, May 16-18), ASCI.

Weickert, J., 1997, A review of nonlinear diffusion filtering: in B.t.H. Romeny, L. Florack, J. Koenderink and M. Viergever, eds., Scale-Space Theory in Computer Vision, Lecture Notes in Computer Science, Springer, **1252**, 3-28.

Whitcombe, D., and Hodgson, L., 2007, Stabilizing the low frequencies: The Leading Edge, **26**, 66-72.

Whitcombe, Hodgson, L., Hoeber, H., and Yu, Zhou, 2008, Frequency dependent, structurally conformable filtering: Presented at the 78nd Annual International Meeting, SEG.