A structure-guided and edge-preserving algorithm for smoothing 3D seismic data

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Abstract

We present structure-oriented and edge-preserving algorithms for denoising seismic data volumes in the frequency-space (fxy) domain. After transforming the 3D data to the fxy domain, we apply for each frequency slice, 1D edge-preserving smoothing filters which are guided spatially by the so-called gradient structure tensor. The synthesis of the denoised data shows that incoherent as well as footprint noise can be significantly reduced with no loss of important structural information. The algorithm can be efficiently implemented using linear convolutions to compute the structure tensor and simple 1D edge-preserving operators. Contrarily to other 2D and 3D edge preserving algorithms, the proposed filtering is not limited to impedance data volumes.

Introduction

The gradient structure tensor (GST) has been introduced in image analysis for the detection of lines, edges and corners (Faraklioti and Petrou, 2005). The GST has been successfully applied for seismic interpretation as well. In this sense, Randen et al. (2000) and Bakker (2002) applied the GST for the determination of dip and azimuth as well as for highlighting the continuity of seismic events through coherence attributes. On the other hand, Machado and Cunha (2015) used the GST for structure oriented filtering, and Loginov et al. (2016) for stacking microseismic data.

Figure 1 considers a synthetic example of a 2D unit amplitude sinusoidal function (the image has a size of 50x50 pixels). This figure displays the field of orientations which are derived from the GST. As shown, they are parallel to the crests and valleys of the data. Smoothing along these orientations is the basic idea of the structure oriented filtering (SOF).

To smooth data without degrading edges and discontinuities is often very desirable. A simple and efficient way to achieve this properly is given by means of the edge preserving algorithm (EPS) of Luo et al. (2002). The idea of the EPS is to remove noise without blurring edges using an operator that replaces each point of the signal by the average of the most homogeneous segment in its neighborhood. The neighborhood of the sample point to be filtered is defined by the length of the EPS operator, L, which is the only parameter introduced by this algorithm. The data homogeneity is measured by the standard deviation of the

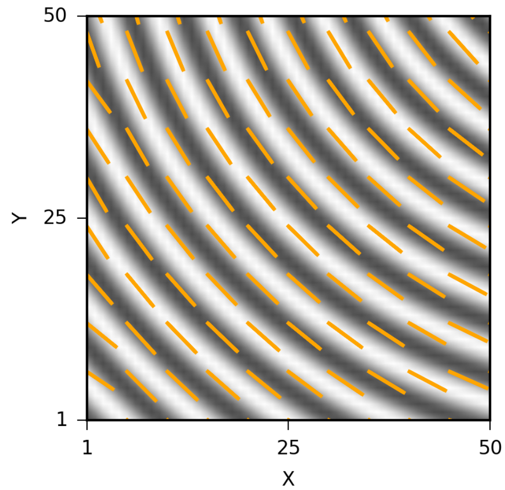

Figure 1 *– Synthetic example of a 2D sinusoidal signal. Orientations along the structures are derived from the smoothed GST eigenvectors* v *(color lines).*

samples within the operator length. In a similar fashion, the linear EPS (LEPS) or first-order edge polynomial fitting (Lu and Lu, 2009), considers the fitting of a straight line in each neighborhood of the point to be filtered. The output is the fitted point with the straight line that gives the lowest misfit of all the overlapping segments of length L that include the point of interest.

Figure 2 illustrates the behavior of EPS and LEPS for filtering the same 1D noise free signal of unit amplitude considered by Lu and Lu (2009). Contrarily to the LEPS result, the EPS output exhibits the characteristic staircase character due to the local fitting of the signal by a constant, which would be better suited for blocky signals (e.g., impedance data). Note that the random noise is attenuated by the two filters without blurring the jump at sample 100. In this example, we selected a filter length of 10 samples for both filters, since this value is closer to the practical length applied in the real datasets. In the example of Figure 2, better results can be obtained by increasing the filter length, as demonstrated by Lu and Lu (2009). It is worth mentioning that the EPS and LEPS were applied by these authors in the time-offset domain to filter 2D seismic sections along orientations given by different scanned velocities over a user-defined range.

An extension of the EPS to 2D and 3D for seismic applications has been presented by AlBinHassan et al. (2006). These filters give as output the mean of the region with lowest standard deviation. The neighborhood of the 2D EPS is a plane centered at the point of interest, which should be tilted in the direction of higher coherence. Three basic operators, a square, a pentagon and a hexagon, with their

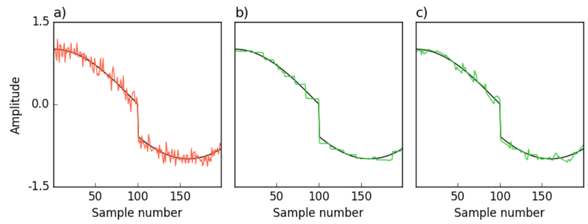

***Figure 2** – a) Noisy signal (random noise of amplitude 0.2). b) and c) Signal after EPS and LEPS, respectively. The black line is the noise-free signal.*

respective rotations, cover all directions around the point to be filtered. Similarly, the 3D EPS is calculated on a cube centered at the point of interest. There are four basic types of operators that, taking into account their rotations, cover all possible directions around the point of interest, making dip steering unnecessary. Both of these algorithms are better suited for denoising seismic impedance data rather than amplitude data (AlBinHassan et al., 2006).

It is widely regarded that spectral decomposition by means of the discrete Fourier transform (DFT) provides a means of utilizing seismic data for interpretation (e.g., Partyka et al. (1999)) and processing by frequency slice filtering (FSF) (Hodgson et al., 2005). In principle, FSF entails transforming the temporal axis of the data into the frequency domain, applying a spatial operator at each frequency slice and returning to the original domain. A recent application of the EPS restricted to the frequency-offset domain for denoising seismic sections can be found in the work of Gómez and Velis (2016).

In this work we introduce a structure oriented filtering algorithm that couples the GST with the EPS/LEPS filters in the fxy domain for denoising 3D seismic data with edge preservation. Each frequency slice (real and imaginary parts) is processed separately as independent images. The method is described in the next section. An application to a real dataset is then given and discussed.

Method

The gradient structure tensor (GST) is defined as the tensor product of the data gradient. Its expression is

$$\mathbf{T} = \begin{bmatrix} g_x{\cdot}g_x & g_x{\cdot}g_y \\ g_x{\cdot}g_y & g_y{\cdot}g_y \end{bmatrix}, \tag{1}$$

where g_x and g_y are the gradient components with respect to the horizontal and vertical directions of the 2D image, respectively.

Since the GST is positive definite, closed form expressions can be easily derived for the eigenvalues and the orthogonal eigenvectors. This means that linear algebra subroutines for the computation of these quantities and the sorting of the eigenvalues are not required. For a point $p = (i, j)$ of the seismic image, the 2×2 matrix representation of the GST is given by

$$\mathbf{T}_p = \begin{bmatrix} T_{11} & T_{12} \\ T_{12} & T_{22} \end{bmatrix}. \tag{2}$$

The eigenvalues of the GST expression 2 are $\lambda_{1,2} = \mathrm{tr}(T) \pm r$, where $\mathrm{tr}(\mathbf{T}_p) = T_{11} + T_{22}$ is the trace of the GST and $r = \sqrt{(T_{11} - T_{22})^2 + 4T_{12}^2}$, what implies that $\lambda_1 \geqslant \lambda_2$. Then $\mathbf{u}_p = (2T_{12}, T_{22} - T_{11} + r)$ and $\mathbf{v}_p = (T_{22} - T_{11} + r, -2T_{12},)$ are the eigenvectors perpendicular and parallel to the local structure, respectively, at point p. From the eigenvalues, the so-called anisotropy parameter,

$$A = (\lambda_2 - \lambda_1)/(\lambda_2 + \lambda_1), \tag{3}$$

can be calculated. This attribute takes values between 0 and 1, and indicates how much the local data around the point p resembles a linear structure (Bakker, 2002).

Local and chaotic microstructure details which can perturb the eigenvector field v are bypassed by smoothing the GST components (Faraklioti and Petrou, 2005),

$$\mathbf{T}^s = \begin{bmatrix} \langle g_x{\cdot}g_x \rangle & \langle g_x{\cdot}g_y \rangle \\ \langle g_x{\cdot}g_y \rangle & \langle g_y{\cdot}g_y \rangle \end{bmatrix}. \tag{4}$$

The computation of the smooth GST 4 can be reduced to simple linear convolutions with a 1D filter, (e.g., a Gaussian operator).

The computation of g_x and g_y can be obtained by means of a Gaussian first derivative filter. This implies that another filter length has to be selected. A common alternative is to apply a simple linear convolution with the difference operator $[-1, 0, +1]$ in the vertical and horizontal directions; if desired, a Sobel gradient can be obtained afterwards by convolving the gradient components with the smoothing mask $[1, 2, 1]$.

In order not to blur structural edges, the smoothing filter should be guided in the orientation given by the eigenvectors $\mathbf{v}$. The use of EPS or LEPS filters ensures that if the operator length L includes an edge, for example, from a buried channel or a fault, no smoothing will be performed across the discontinuity.

An adaptive EPS/LEPS filter can be designed if the filter length is expressed by $L_A = \max(A_{\min}, A)L$. This turns the smoothing filter sensible to the local anisotropy, taking a neighborhood of length $2L - 1$ original data samples where $A = 1$ (meaning that structures are well defined), while reducing to $2A_{\min}L - 1$ if the data is locally noisy with no clearly defined linear structures. If $A_{\min} = 0$ the filtering does not globally attenuates random noise and localizes the denoising only along important seismic structures. We consider in this work $A_{\min} = 0.5$ to obtain random noise reduction for every data point.

Depending of the point-to-point orientation of the eigenvector $\mathbf{v}$, an appropriate interpolation is required in order to apply the 1D edge preserving operator. We chose bilinear or nearest neighbor interpolation because of their simplicity and low computational cost.

Due to the hermitian property of seismic data in the frequency domain, only one half of the total number of frequency samples of the frequency-space seismic cube are needed for filtering. Furthermore, the information denoised and preserved at each frequency slice contributes to the improvement of the signal–to–noise ratio at all time samples.

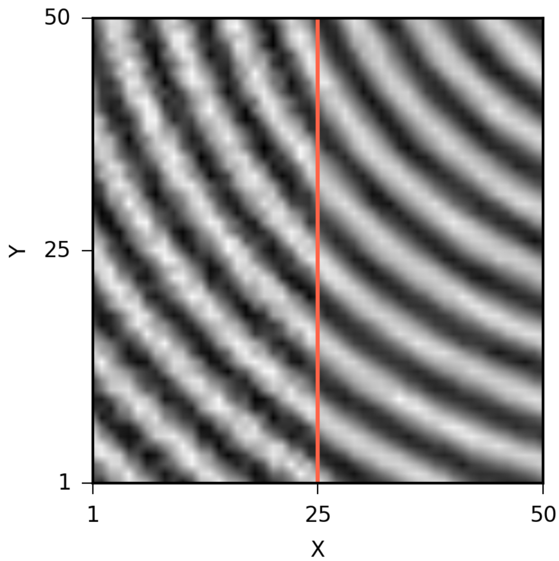

***Figure 3** – Synthetic example of a 2D noisy sinusoidal signal. Left of $X = 25$ noisy data, right of $X = 25$ denoised by GST LEPS.*

We remark that all that is required for the gradient calculations and the GST smoothing are linear convolutions, which can be efficiently implemented.

Figure 3 shows the 2D sinusoidal function of Figure 1 with added random noise of maximum amplitude 0.7 and the result from running LEPS guided by the smoothed GST depicted in Figure 1. The filter length is the gradient is calculated by a Gaussian first derivative operator of length 5 and the structure tensor is smoothed with a Gaussian filter of length 7. We observe that the random noise has been reduced without degrading the delineations of the signal.

Real data example

To show the performance of the proposed algorithm, we consider a public available 3D seismic offshore data volume from Sable Island Canada, which is owned by the Nova Scotia Department of Energy (Nova Scotia Department of Energy, 1992). Similar to Kington (2015), we focus the demonstration of our algorithm on a subset of 250 inlines, 200 crosslines and 55 time samples at a sample rate of 4 ms. Figure 4 shows the orientation fields for the real and imaginary parts of the frequency slice at 22.7 Hz. A Gaussian derivative of $2M + 1 = 21$ points and standard deviation of $M/4$ is used for computing the gradient and a Gaussian filter of 31 coefficients for smoothing the corresponding GST. We observe that the orientations follow the main structural features of the frequency slice. These orientations will be subsequently used for steering the LEPS filter at every point of each frequency slice. In a practical context, the field of orientations obtained from the eigenvectors $\mathbf{v}$ alongside the structures at each frequency slice can be inspected by the interpreter to assess if the tensor smoothing is appropriate to the objectives of the denoising.

Figure 5 illustrates the filtering process and the selection of parameters. The figure presents a portion of the real part

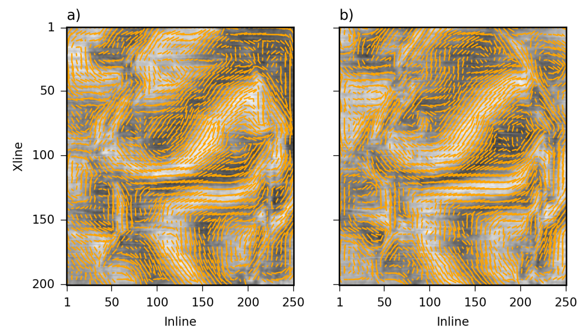

***Figure 4** – a) Real part and b) imaginary part of the frequency slice at $f = 22.7$ Hz from the seismic 3D data. Orientation along the structures are derived from the smoothed GST eigenvectors $\mathbf{v}$ (color lines).*

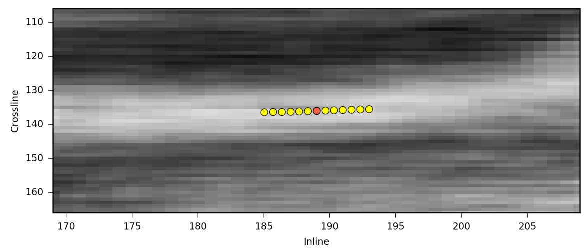

***Figure 5** – Portion of the real part of the frequency slice at $f = 22.7$ Hz from the seismic 3D data. The center point (red) is to be filtered by LEPS with $L_A = 7$. A total of $2L_A - 1$ points are considered for filtering using the neighboring yellow points, which are oriented by the smooth GST eigenvector field $\mathbf{v}$.*

of the frequency slice considered in Figure 4a. The center point is to be smoothed by LEPS with $L = 10$. The anisotropy at the center point is 0.7, then the filter length L_A is seven data samples long. A number of $2L_A - 1$ points are taken at each side of the sample of interest, some of which may be interpolated if they do not fall on original data samples. Figure 6 shows the whole frequency slice depicted in Figure 4a before and after the GST LEPS denoising. We observe that a global reduction of horizontal footprint lines and a sharper delineation of the structural boundaries are attained.

After every frequency slice up to 60% of the Nyquist frequency is processed, the filtered seismic amplitudes in the original time-space domain are obtained by the inverse DFT. A time slice at 0.02 s of the final result is presented in Figure 7. The removal of footprint energy and random noise attenuation are evident, improving the signal–to–noise ratio of the image, enhancing the spatial continuity of the geological structures and increasing the image sharpness.

For comparison, Figure 8 shows the results obtained by means of the application of the 2D EPS on the space-frequency domain (FXY) and of 3D EPS to the data amplitudes. The 2D FXY EPS is calculated within an planar neighborhood of 5×5 samples on every frequency slice. The 3D EPS is calculated on every $5 \times 5 \times 5$ cube centered at the point of interest in the space-time domain. Contrar-

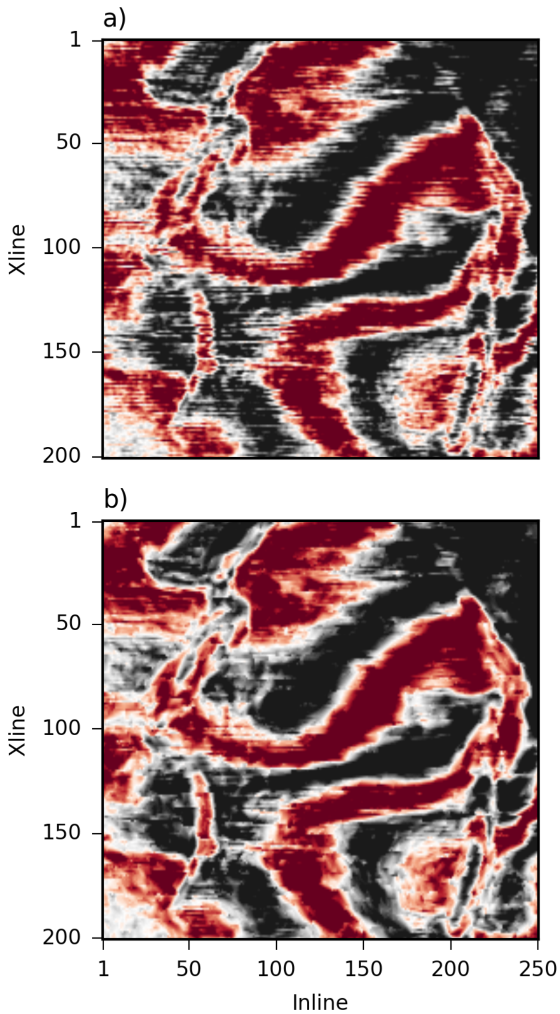

***Figure 6** – a) Real part of a frequency slice a) before and b) after GST LEPS denoising.*

ily to the results of the GST LEPS filtering (Figure 7b), we note that noise reduction of 2D FXY EPS is not as effective as GST LEPS filtering, while amplitudes and structures are severely compromised for 3D EPS. This last result clearly shows that the application of the 3D EPS filter in the time domain are better suited for impedance data, where vertical discontinuities are expected to occur (AlBinHassan et al., 2006).

Conclusions

An algorithm for noise attenuation with edge preservation has been introduced and tested on a real seismic dataset. The method we propose works by frequency slice filtering and spatial edge preservation smoothing. The smoothing is oriented along structures with the aid of a smooth gradient structure tensor. The result of this process shows a significant potential for footprint reduction and structural enhancing. The proposed method can be applied as a preconditioning step previous to the computation of standard semblance-based attributes. The algorithm relies on closed-form expressions for the eigenvector field computa-

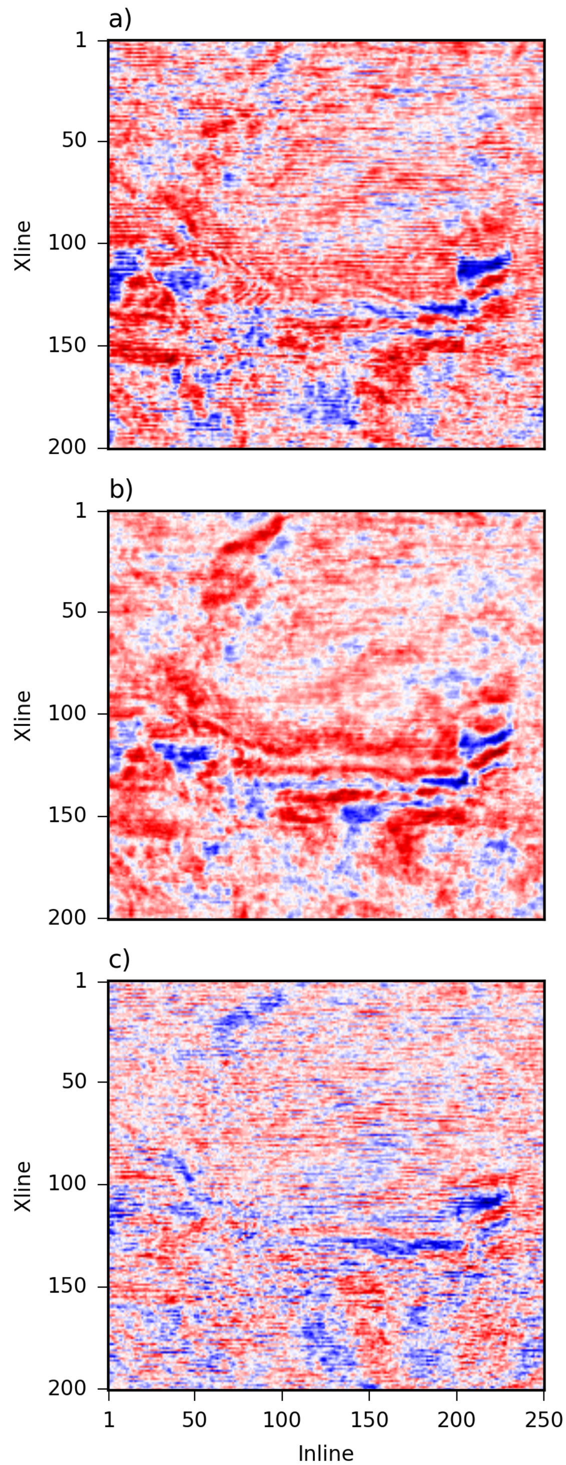

***Figure 7** – A time slice of the seismic amplitude volume a) before and b) after the GST LEPS filtering. c) Difference.*

tion and the use of simple 1D linear convolutions for tensor smoothing and frequency slice computations, a feature that makes it computationally efficient.

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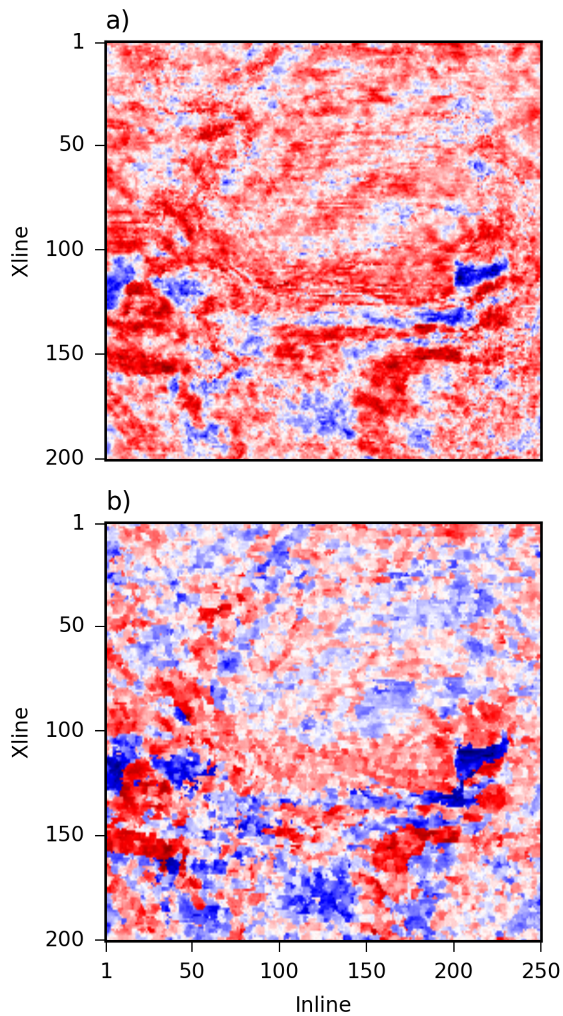

***Figure 8** – The time slice of Figure 7a , a) after 2D FXY EPS and b) after 3D EPS.*