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Fast structural interpretation with structure-oriented filtering

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ABSTRACT

We present a new approach to structural interpretation of 3D seismic data with the objectives of simplifying the task and reducing the interpretation time. The essential element is the stepwise removal of noise, and eventually of small-scale stratigraphic and structural features, to derive more and more simple representations of structural shape. Without noise and small-scale structure, both man and machine (autotrackers) can arrive at a structural interpretation faster. If the interpreters so wish, they can refine such an initial crude structural interpretation in selected target areas.

We discuss a class of filters that removes noise and, if desired, simplifies structural information in 3D seismic data. The gist of these filters is a smoothing operation parallel to the seismic reflections that does not operate beyond reflection terminations (faults). These filters therefore have three ingredients: (1) orientation analysis, (2) edge detection, and (3) edge-preserving oriented smoothing. We discuss one particular implementation of this principle in some detail: a simulated anisotropic diffusion process (low-pass filter) that diffuses the seismic amplitude while the diffusion tensor is computed from the local image structure (so that the diffusion is parallel to the reflections). Examples show the remarkable effects of this operation.

INTRODUCTION

This paper addresses a new approach to structural interpretation of 3D seismic data. Without the mathematics, this article also appeared in *The Leading Edge* (Höcker and Fehmers, 2002). The discussed method and workflow should be viewed against a background of recent changes in the working environment for seismic interpretation. For instance, because there has been constant pressure to reduce study tumaround times or at least to come up quickly with preliminary results in support of investment decisions. Integrated teams have been set up to analyze problems in parallel rather than in sequential workflows. For the seismic interpreter, this means changing from a one-time handover of final results to a repetitive process of feeding data into iterative team processes, starting with a crude structural model and followed by increasingly detailed and sophisticated models.

As another change, geologists have more and more replaced geophysicists in seismic interpretation. This trend has certainly improved the geological feasibility of the average interpretation, in particular with noisy data where defendable answers to ambiguity can only be found by testing alternative geological scenarios. However, the change has also lead to frequent overinterpretation of noisy data. Structural and stratigraphic phenomena have been seen in coherent noise patterns, as demonstrated convincingly by Hesthammer (1999). In part, the problem relates to the fact that geologist interpreters easily accept 3D seismic data delivered to them by seismic processors as the best possible product because they lack detailed knowledge of the geophysical problems and are intimidated by the numerical sophistication behind the product.

Both acceleration of interpretation and handling of noisy data would be helped by functionality that stabilizes and simplifies 3D seismic data. Preferably such functionality should be at the fingertips of interpreters, to empirically find the best solution for a given task, rather than as a once-off step in seismic processing.

The need for further evolution of seismic interpretation methods and software has only been partially met by vendors. Focus has long been on data integration, with little progress in the interpretation technique as such. As a result, vendors can now offer an interpretation toolkit that is mature for "multi-2D" interpretation but, with the exception of 3D visualization, little progress has been made in true 3D interpretation techniques. Pace-making developments such as body-tracking (Hoogenboom et al,. 1996) and coherency technology (Bahorich and Farmer 1995) have been developed by the oil industry rather than by suppliers. We have been fortunate to be part of a longstanding research effort into methods that facilitate faster assessment and interpretation of 3D seismic data,

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incorporating image processing techniques on top of more traditional geophysical processing research.

DATA CONDITIONING FOR STRUCTURAL INTERPRETATION

Seismic processing parameters are usually chosen such that the resulting data can serve a number of interpretation activities equally well although the specific requirements of individual interpretation tasks may differ greatly. Hydrocarbon detection, quantitative prediction, and stratigraphic interpretation benefit from "true" amplitudes and a high bandwidth of the seismic data. In contrast, structural interpretation is facilitated by high event continuity and good lateral resolution of event terminations at faults.

Data conditioning for a specific interpretation task means removing the undesired and unnecessary, while improving the representation and interpretability of those parts of the information that are essential for the task (Figure 1). Consequently, data conditioning simplifies and accelerates the task at hand. It can also greatly facilitate the application of automated interpretation techniques (Figure 2). As data conditioning is tailored to a specific interpretation task, the generated volumes are not meant to replace the original but will coexist with it as transient or permanent versions.

Some data conditioning can be achieved with relatively simple filters. For instance, removal of high frequencies with a simple low-pass filter can significantly improve detectability and interpretability of faults [for examples and discussion see Hesthammer (1999)]. However, more spectacular results have been achieved with the dedicated structure-oriented filter (SOF) technology described below.

STRUCTURE ORIENTED FILTERING

Traditionally, poststack seismic data have only been filtered in geometries that are aligned with the seismic grid—the simplest case of a grid-oriented filter being a seismic trace filter. Good examples for 3D grid-oriented filters are simple coherency-type measurement that are based on comparison of amplitudes between traces in horizontal direction, usually in vertical windows of 5–25 seismic samples. However, it was realized early on that 3D grid-oriented filters have severe limitations in the presence of structural dip. In an internal Shell publication, Dick Dalley wrote in 1994, "Rock bodies [as represented by seismic data] know nothing of the grid with which they have been sampled and it makes no sense to make spatial measurements along the grid orientation other than those related to structure, such as Dip and Azimuth. Measurement intended to reveal stratigraphic/porefill information should be oriented along or perpendicular to local structure." This statement also holds for poststack noise suppression; the reliability of a single seismic sample can best be tested by comparing the amplitude value against equivalent data on neighboring traces (equivalent means here following the structural dip).

Figure 3 demonstrates the effect of oriented smoothing on (3D) seismic data. Unconstrained structure-oriented smoothing stabilizes reflections but has a devastating effect on the expression of faults since reflection terminations are removed (Figure 3a–d). In order to be useful, some kind of edge preservation must be introduced into the filtering process (Figure 3 e–h).

In short, successful application of oriented smoothing to seismic data requires three ingredients: (1) orientation analysis (determination of the local orientation of the reflections), (2) edge detection (determination of possible reflection

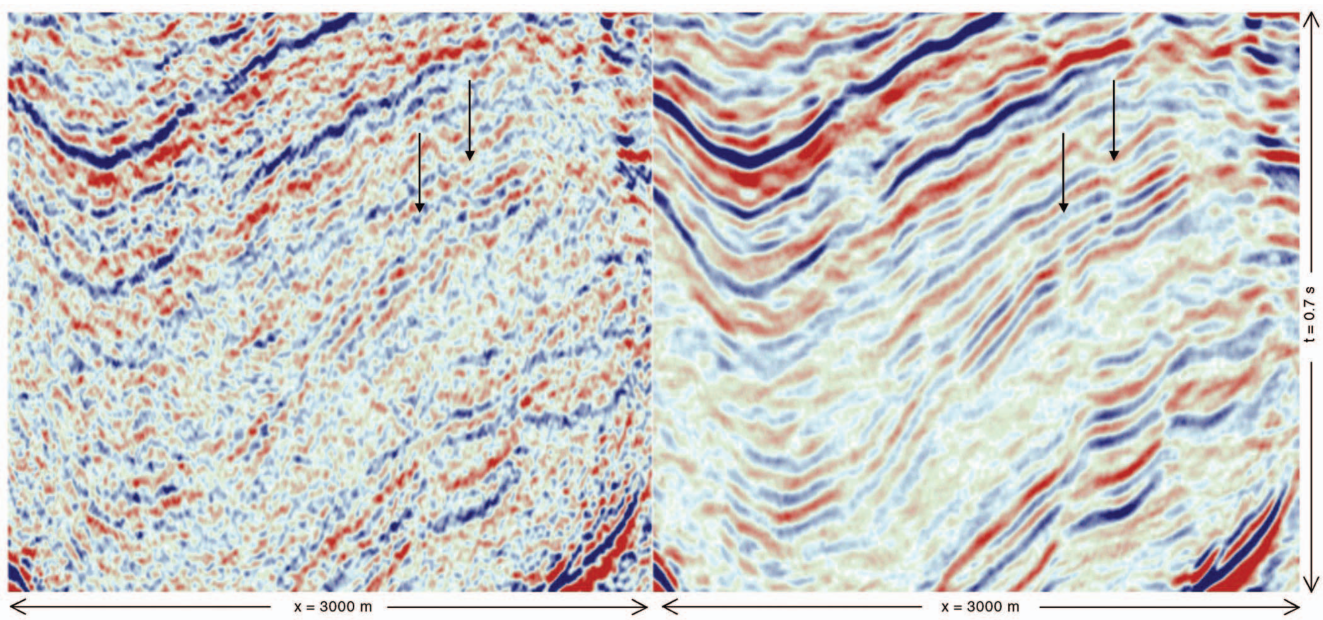

FIG. 1. Data conditioning for structural interpretation [by, structure oriented filter—edge preserving (SOF-EP)]. Structure-oriented filtering has stabilised the broken-up nature of reflections in the original data ("pearl string reflections") (left) into continuous and trackable events (right). Other amplitude variations of similar magnitude were found to be laterally consistent and were maintained as event terminations against faults (arrows).

terminations), and (3) smoothing with edge preservation (smoothing of the data in the direction of the local orientation, without filtering across detected edges). Each of these steps can be performed in a multitude of ways and has been explored in the academic realm, however, without optimization for noise suppression in seismic data.

Many image processing publications report on methods for analyzing the orientation in images, with a noteworthy contribution on wood images and fingerprint reconstruction from Schlumberger (Kass and Witkin, 1987). Known methods include Gabor filters, windowed Fourier analysis, the local gradient, local Radon (Hough) transform, and correlation techniques. Oriented smoothing as part of image processing has only been documented since the 1990s, notably reflecting on a method called anisotropic diffusion, pioneered by Weickert (1998).

With our colleagues, we have implemented edge-preserving oriented smoothing in two fashions. A first algorithm extracts a 2D platelet of seismic amplitudes from 3D seismic data, following the local structure. Edge-preserving smoothing is then applied to the data of this platelet, with the result written back into a 3D output cube. In edge preservation tests, it was found that simple median filters become inadequate when the filter size increases. Better edge preservation performance was achieved with Kuwahara-type methods (Kuwahara et al., 1976; Nagao and Matsuyama, 1979) in which a possible edge is detected by computing the statistics over a set of subregions. Subregions showing deviating statistics are likely to contain edges and are assigned smaller weights in filtering. This filter, developed in 1997 is known at Shell as Structure-Oriented Filter-Edge Preserving (SOF-EP).

The second generation of edge-preserving oriented smoothing was developed in 1999. It is based on a 3D implementation of the anisotropic diffusion technique and, in reference to the example of Figure 4, we have called it the "Van Gogh" filter. The advantage of this method is that it can be carried much further than SOF-EP filtering. Figure 5 shows that initial application of the Van Gogh filter suppresses incoherent noise and small stratigraphic features. The continuity of events is enhanced while the acuity of faults is preserved or even improved. By applying more diffusion steps, the Van Gogh filter simplifies the structural image; undulating reflections are gradually straightened and minor fault-like features vanish—whether real or not. Ultimately the structure is simplified to its most rudimentary form.

ALTERNATIVE WORKFLOW FOR STRUCTURAL INTERPRETATION

We believe that data conditioning with the Van Gogh filter is highly supportive of novel workflows in structural interpretation. Having stored not only a final version but also a number of intermediate diffusion steps (Figure 5), interpretation can start on the most simplified version and be refined on intermediate or unfiltered versions. Such representation of structural shape and complexity at various scales is an example of the so-called scale-space approach in image processing (Lindeberg 1994), which has been developed to facilitate rapid machine interpretation.

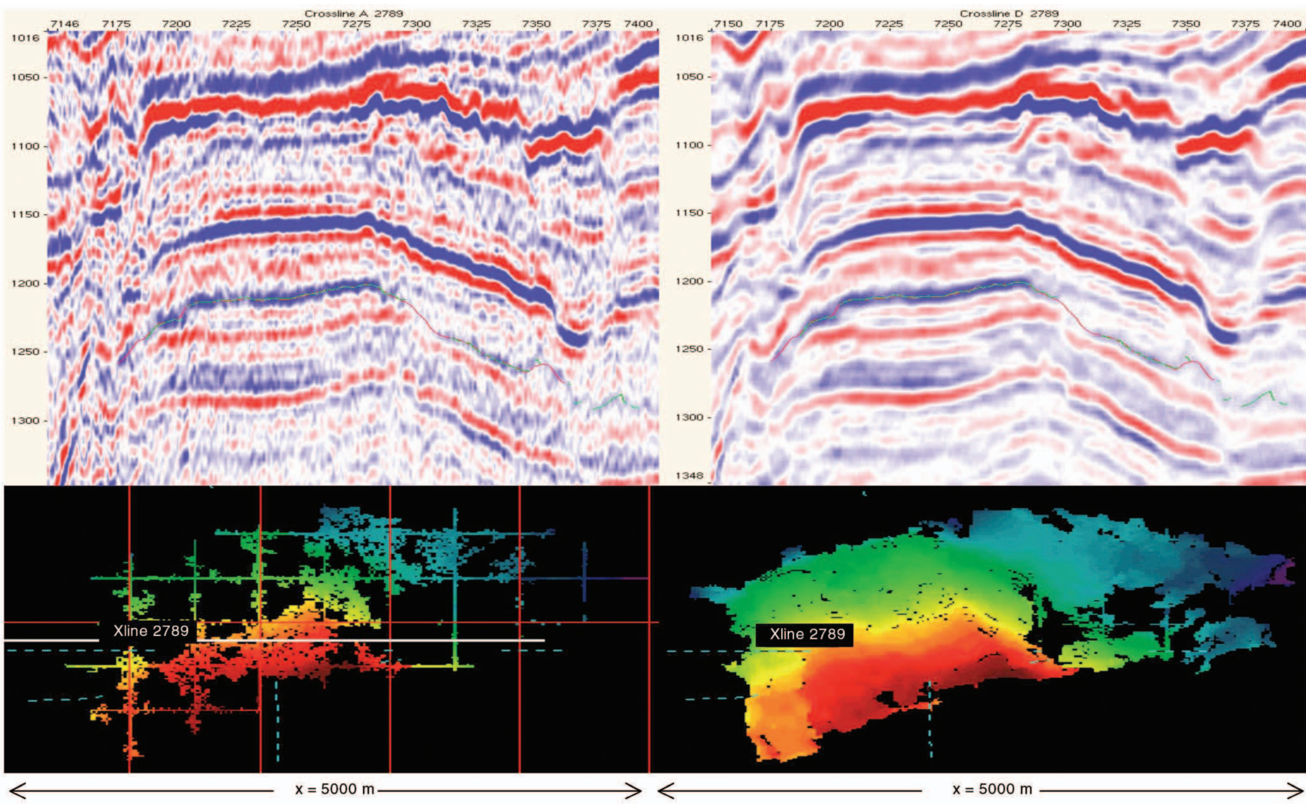

FIG. 2. Data conditioning improves and accelerates seismic interpretation tasks such as autotracking. (Top left) Crossline through original seismic data. (Top right) Crossline through SOF-EP filtered seismic data. (Bottom left) Depth map of horizon autotracked on original seismic data. (Bottom right) Depth map of horizon autotracked on filtered seismic data.

Automated tracking methods convert the simplified seismic image quickly into a discrete model of faults and horizons: a first structural model that is already quite complete in its crudeness. This model can be passed on to geologists and reservoir engineers for analysis, to identify those model elements that are most relevant in controlling trapping configuration, dynamic reservoir behavior or, ultimately, economic performance of the asset. A second iteration of interpretation will then be

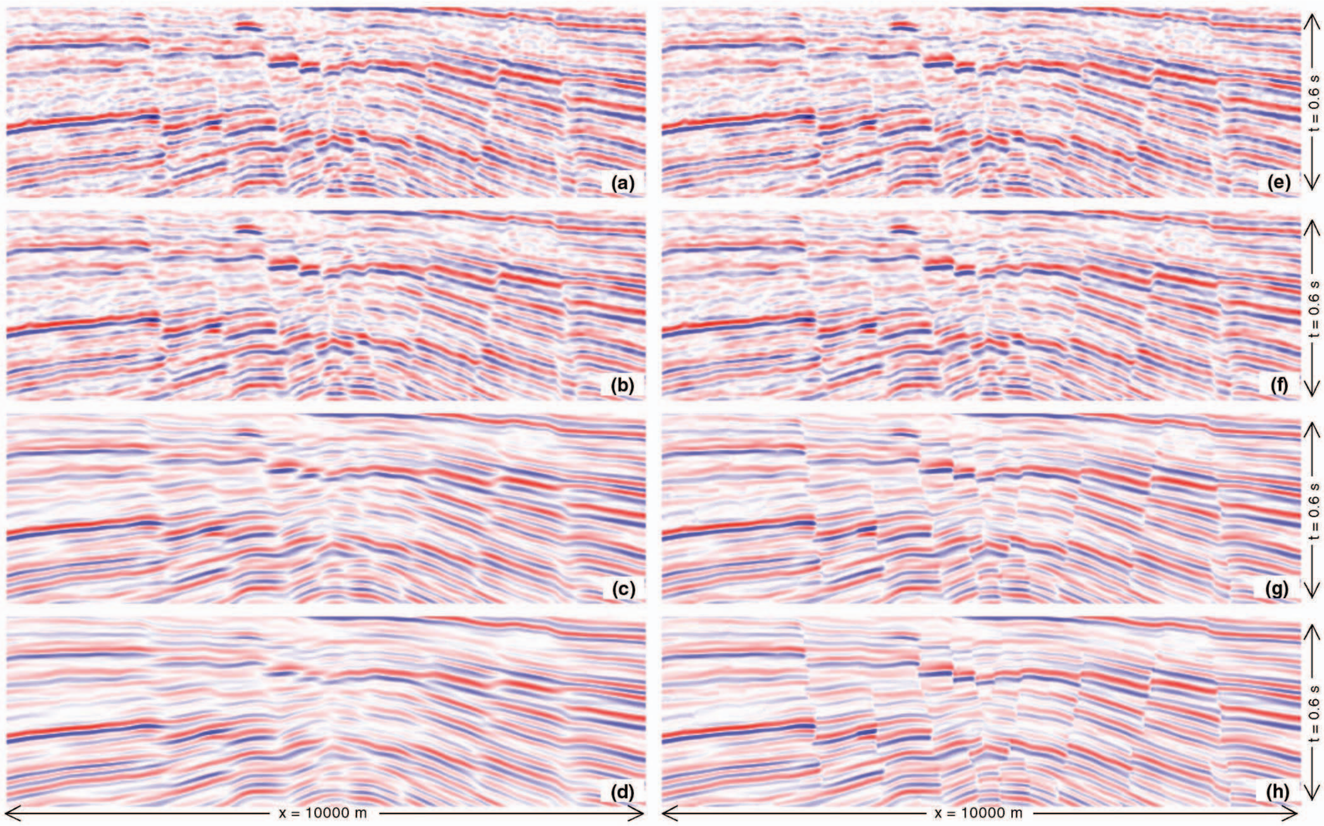

FIG. 3. Anisotropic diffusion on 3D seismic without (a–d) and with (e–h) edge preservation. From top (a and e) to bottom (d and h): 0 (input), 1, 4, and 9 diffusion steps, respectively.

FIG. 4. Structure-oriented filtering applied to a self portrait of the Dutch painter Van Gogh. Anisotropic diffusion (left to right): input, 100, and 10,000 diffusion steps, number of steps is not comparable to other examples due to differences in implementation.

targeted at increasing the detail of relevant model elements by interpreting a more moderately filtered version of the data. Also, this pass can be executed quickly as it is largely a "snapping" process (e.g., an automated adjustment of horizon picks to event position in less filtered data). More iterations may follow if required to analyze and understand the prospect or reservoir at an appropriate level of resolution. However, the cumulative interpretation will, on average, be shorter than with conventional approaches to structural interpretation.

The automated interpretation and modeling tools currently available from vendors are not necessarily suitable to support a rapid transformation of simple seismic images into structural models. With conditioned data, the task of automated fault tracking is much simpler, due to increased contrast of fault highlighting products such as coherence cubes. Automatic horizon trackers can be modified to profit from the increased phase stability of conditioned data, for instance, improving performance in the presence of doublets or long-wavelength changes in event characteristics. Most essential, however, is the development of fast methods for building topologically consistent models from heretofore unrelated faults and horizons.

The remainder of this paper discusses technical aspects of the Van Gogh filter. We have chosen to elaborate on this filter rather than another implementation for three reasons. These are its clear mathematical basis (a partial differential equation), its intuitive understanding (as a diffusion process), and the natural appearance of the notion of scale.

THE VAN GOGH FILTER

The Van Gogh filter simulates an anisotropic diffusion process, where the input (seismic) image serves as the initial condition, and the processed image is given by solving a partial differential equation through time. Anisotropic diffusion for image processing was pioneered by Weickert in his 1996 dissertation (see Weickert, 1998) and the discussion largely follows his argument. We all have an intuitive understanding of diffusion.

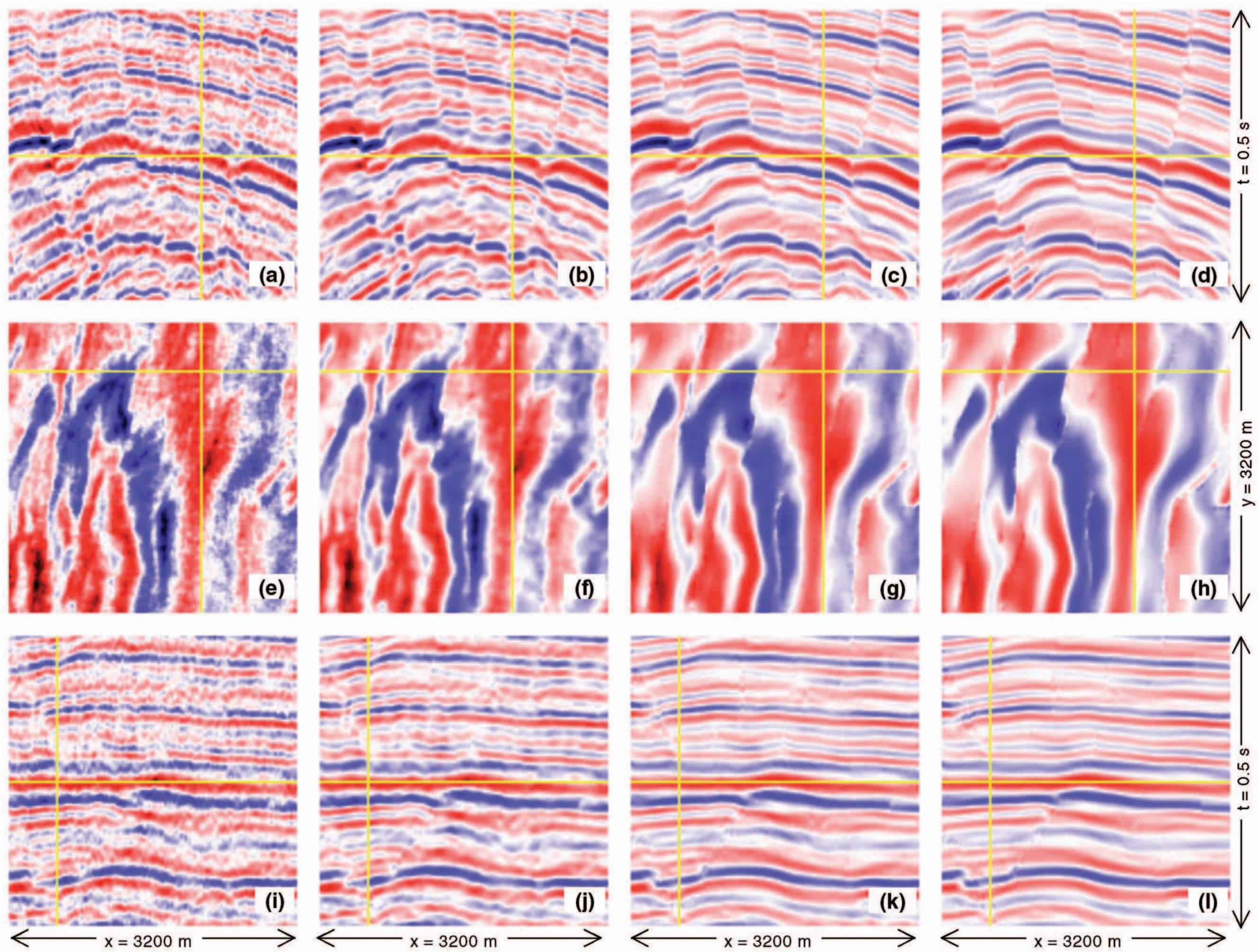

FIG. 5. Anisotropic diffusion results in common seismic displays [dip line (a–d), time slice (e–h), strike line (i–l)]. From left to right, the geological structure comes out ever more clearly. The Van Gogh filter first removes incoherent noise (the spotty reflections become more continuous). Next, it suppresses structural details of small scale, then of a somewhat larger scale. For interpreters, this effect is apparent in the straightening of the reflections and, more so, in the gradual disappearance of the minor faults. From left (a,e,i) to right (d,h,l): 0 (input), 1, 4, and 9 diffusion steps, respectively.

Diffusion is a physical process that balances concentration (or temperature) differences without creating or removing mass (or heat). In our application, we apply diffusion to images and, instead of concentration or heat, we use seismic amplitude. Time is an inherent parameter in the diffusion process. At time $\tau = 0$, we start with the input image. The longer the diffusion proceeds in time, the stronger the image is filtered.

Here follows the essential mathematics. The gradient in seismic amplitude causes a flux from the highs to the lows. The flux vector $\mathbf{j}$ is given by Fick's law,

$$\mathbf{j} = -\mathbf{D}\nabla u, \tag{1}$$

where ∇u is the gradient of seismic amplitude u, and $\mathbf{D}$ is the diffusion tensor, a symmetric and positive semidefinite tensor. If $\mathbf{j}$ and ∇u are parallel, $\mathbf{D}$ can be replaced by a scalar (the diffusion coefficient or diffusivity), and we call this situation isotropic diffusion. In the general case, $\mathbf{j}$ and ∇u are not parallel, and the diffusion is anisotropic.

The fact that diffusion should not create or remove mass (the average seismic amplitude should not change) is expressed by the continuity condition,

$$\frac{\partial u}{\partial \tau} = -\nabla \mathbf{j}, \tag{2}$$

where τ stands for time (not related to seismic recording time), and $\nabla \mathbf{j}$ is the divergence of the flux. When we plug Fick's law into the continuity condition, we arrive at the diffusion equation:

$$\frac{\partial u}{\partial \tau} = \nabla(\mathbf{D}\nabla u). \tag{3}$$

The whole effect of the diffusion depends upon the choice of the diffusion tensor $\mathbf{D}$:

1) $\mathbf{D}$ is scalar and $\mathbf{D} \neq \mathbf{D}(u)$. This is the simplest form. The diffusion equation is linear $[\mathbf{D} \neq \mathbf{D}(u)]$ and isotropic ($\mathbf{D}$ is scalar). In this case, it can be shown that the diffusion corresponds to low-pass nonadaptive filtering with a Gaussian kernel whose width increases with the square root of time ($\sigma \propto \sqrt{\tau}$). This is the natural appearance of scale referred to earlier (see Figure 6b).
2) $\mathbf{D}$ is scalar and $\mathbf{D} = \mathbf{D}(u)$. When the diffusion equation is nonlinear, that is, the diffusivity depends on the local image structure $[\mathbf{D} = \mathbf{D}(u)]$, we get more interesting results. Nonlinear isotropic diffusion was introduced to image processing by Perona and Malik (1990). Its most important application is edge-preserving smoothing (see Figure 6c). Nonlinear diffusion can be compared to adaptive (low-pass) filtering in the sense that the smoothing kernel depends on the local image structure.
3) $\mathbf{D}$ is tensor and $\mathbf{D} = \mathbf{D}(u)$. The diffusion tensor introduces anisotropy to the diffusion by treating different orientations differently: diffusion is allowed in some directions and inhibited in others. It makes sense to align the principal axes of the diffusion with the orientations of the image. In other words, $\mathbf{D}$ is constructed such that its eigenvectors follow the local orientation of the image. This leaves many options for $\mathbf{D}$ because we can still adjust the eigenvalues of $\mathbf{D}$. In images where orientation carries the bulk of the information (like fingerprints and seismic images), interesting results are obtained when diffusion (i.e., smoothing) is allowed only along the structure (seismic reflections) (see Figure 6d). This can be achieved by properly setting the eigenvalues of $\mathbf{D}$.

Paintings by Van Gogh are very well suited for a demonstration of anisotropic diffusion (Figure 4) because the artist applied the paint in distinct strokes, adding a clear anisotropy to the images. Application of anisotropic diffusion to these paintings has given the method its alias—the Van Gogh filter. Seismic images can be likened to Van Gogh paintings in the sense that they too have a flowlike character. The application of anisotropic diffusion to a seismic image, however, is rather catastrophic from a structural point of view: the faults disappear after a few diffusion steps (see Figure 6d and Figure 3a–d). The remedy to this problem is as simple as it is effective: introduce a continuity factor ε ($0 \leq \varepsilon \leq 1$) into the diffusion equation (3):

$$\frac{\partial u}{\partial \tau} = \nabla(\varepsilon \mathbf{D}\nabla u), \tag{4}$$

where ε approaches zero near a fault and approaches one away from a fault. The fault-preserving effect of the factor ε in the diffusion process is demonstrated in Figure 3e–f.

The following sections explain how we compute the local image orientation (by means of the structural tensor $\mathbf{S}$) and how we compute the diffusion tensor $\mathbf{D}$.

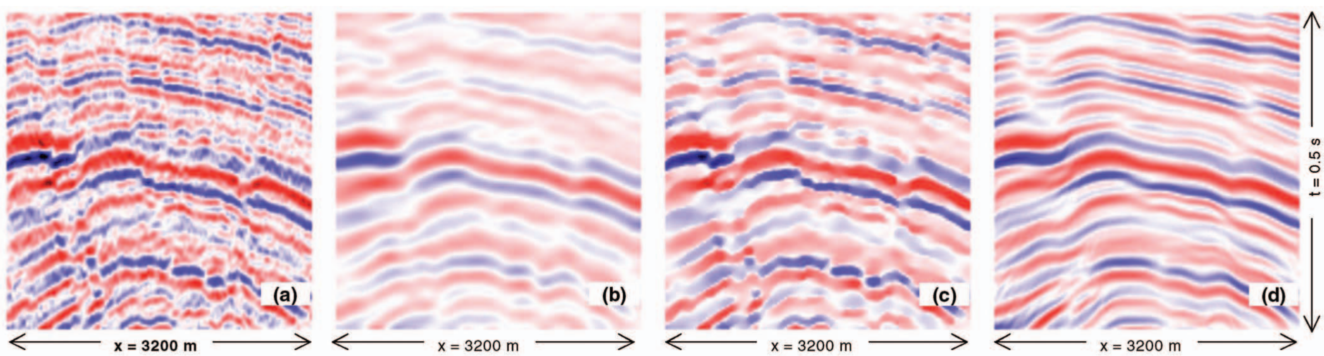

FIG. 6. Different kinds of diffusion applied to seismic data: (a) input, (b) linear diffusion, (c) nonlinear isotropic diffusion (Perona and Malik, 1990), and (d) nonlinear anisotropic diffusion.

THE STRUCTURAL TENSOR

There are many ways to compute the orientation. For the diffusion, it is most economical to use the gradient ∇u because we need that anyway. The gradient is perpendicular to the horizons and thus contains information on the local orientation of the image. When one wants to compute the *average* orientation of the image in a certain region, one cannot average the vector elements piece by piece. To see why this goes wrong, please consider a positive horizontal reflection. On the top side of the reflection, the gradient will point downwards (towards the maximum); on the lower side, it will point upwards (towards the maximum). These two vectors cancel, suggesting loss of orientation, while the orientation is clearly defined. A proper way to average the orientation is via the structural tensor (gradient squared tensor) **S**,

$$\mathbf{S} = \nabla u(\nabla u)^T, \tag{5}$$

where the superscript "T" denotes the transpose. **S** is a positive semidefinite symmetric tensor of rank one [rank one means that of all (i.e., 3) eigenvalues of **S**, one differs from zero]. **S** contains the same information as ∇u, and **S** is the structural tensor at the scale σ of no smoothing, which we define to be $\sigma = 0$. To compute the orientation of the image at a different scale (this is the actual averaging), we are going to apply a low-pass filter to **S**, element by element, over a region determined by the scale parameter σ. This low-pass filter can, for instance, be implemented through a convolution with a positive and symmetrical kernel K_σ ($\mathbf{S}_\sigma = S^* K_\sigma$), where the operation is applied to all tensor elements separately. Now S_σ is the structural tensor at scale σ, giving the orientation structure at the same scale (that is, the scale over which the orientation is averaged). S_σ is a symmetric positive semidefinite tensor [i.e., all eigenvalues are real and larger than or equal to 0 ($\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq 0$), where we have sorted the eigenvalues in decreasing order]. The eigenvectors and eigenvalues of $\mathbf{S}_\sigma$ contain information on the local orientation. This is illustrated by three idealized examples:

1) $\lambda_1 = \lambda_2 = \lambda_3 > 0$. There is no preferred orientation. Any vector is an eigenvector. Hence, the eigenvectors contain no information.
2) $\lambda_1 > \lambda_2 = \lambda_3 = 0$. The system is in a pure orientation eigenstate: the orientation does not change over the smoothing kernel. This indicates a perfectly layered noise-free layer-cake seismic image. The eigenvector corresponding to the single non-vanishing eigenvalue is perpendicular to the reflections.
3) $\lambda_1 > \lambda_2 > \lambda_3 = 0$. This situation indicates a noise-free curved planar structure, such as a syncline or anticline. Again, the eigenvector corresponding to the largest eigenvalue is perpendicular to the reflections. The eigenvector that goes with the smallest eigenvalue is parallel to the crest of the anticline.

The method described here is mathematically almost equivalent to Randen et al. (2000), where the eigenvalues are used to compute various seismic texture attributes.

THE DIFFUSION TENSOR

The construction of the diffusion **D** tensor is simple once we have $\mathbf{S}_\sigma$; their eigenvectors are identical, only the eigenvalues are modified. As $\mathbf{S}_\sigma$ is a symmetric tensor, its spectral decomposition is as follows:

$$\mathbf{S}_\sigma = \sum_{i=1}^{d} \lambda_i \mathbf{v_i} \mathbf{v_i}^T, \tag{6}$$

where $\mathbf{v_i}^T \mathbf{v}_j = \delta_{ij}$, d is the dimension of the image, and $\mathbf{v_i}$ are the eigenvectors, which form a normalized orthogonal basis. The diffusion tensor **D** can now formally be written as

$$\mathbf{D} = \sum_{i=1}^{d} \mu_i \mathbf{v_i} \mathbf{v_i}^T, \tag{7}$$

where $\mu_1 = 0$, $\mu_2 = \mu_3 = 1$. In words, this means that the eigenvectors parallel to the structure get eigenvalues 1, whereas the eigenvalue of the eigenvector perpendicular to the reflections is set to 0. This inhibits diffusion of the seismic amplitude in the direction perpendicular to the reflection, as it should, because diffusion in this direction would quickly destroy the reflections.

THE CONTINUITY FACTOR

There exist many ways to compute a measure of continuity ε. We mention semblance and the coherency cube (Bahorich and Farmer, 1995; Gersztenkorn and Marfurt, 1999). Here, we do not enter the discussion on which is best; rather, we introduce another measure that, in our opinion, is certainly not worse and that is based on the structural tensor. This has the obvious computational advantage that we can reuse some of the intermediate results.

We have seen that the structural tensor carries information on the orientation coherence. This property can be exploited to the fullest when considering the structural tensor at two different scales. The change of structural tensor over scale can be expressed in a continuity factor ε:

$$\varepsilon = \frac{Tr(\mathbf{S}_\sigma \mathbf{S}_\rho)}{Tr(\mathbf{S}_\sigma) Tr(\mathbf{S}_\rho)},$$

where $\mathbf{S}_\sigma$ and $\mathbf{S}_\rho$ are structural tensors at two different scales. The symbol *Tr* denotes the trace, and the tensor product in the numerator is obtained by standard matrix multiplication. It can be shown that $0 \leq \varepsilon \leq 1$, where small values indicate a fault and vice versa.

NUMERICAL IMPLEMENTATION

The Van Gogh (anisotropic diffusion) operation is formulated as an initial value problem defined by a (parabolic) partial differential equation (4), where the input seismic data correspond to the initial value $u_{n=0}$, where the subscript is shorthand for $\tau = n\Delta\tau$, and with Neumann boundary conditions (no flux across image boundaries). We have to solve the equation forward in time. Because this kind of data conditioning filter is applied in the interpretation stage rather than the seismic processing stage, the implementation should be memory and CPU efficient. Of course, it should be stable as well. Strange as it may sound, accuracy is not so much an issue. The purpose is to affect the seismic amplitudes, and it does not really matter whether the change corresponds to the diffusion process exactly.

In our implementation, we used a finite difference scheme because the seismic data are given on a Cartesian grid. The tensor **D** is nondiagonal, and the stencil has 27 entries. In implicit schemes, this leads to a (sparse) matrix with complicated structure, so that efficient solutions are hard to implement. We have not applied time splitting either. These restrictions have led to a basic explicit forward differencing scheme (Euler),

$$u_{n+1} = u_n + \Delta\tau\nabla(\varepsilon_n \mathbf{D}_n \nabla u_n),$$

that can be interpreted as iterative smoothing. To remain stable, explicit schemes usually require a small stepsize $\Delta\tau$ and therefore an excessive number of iterations, but in our applications 1–5 iterations suffice. Some of the intermediate results are computed on a coarser grid, which can be likened to a kind of rudimentary multigrid implementation.

CONCLUSIONS

We have discussed a class of filters that removes noise and, if desired, simplifies structural information in 3D seismic data. These filters apply a smoothing operation parallel to the seismic reflections that does not operate beyond reflection terminations (faults). These filters therefore require three ingredients: (1) automatic orientation analysis, (2) automatic edge detection, and (3) edge-preserving oriented smoothing. Application of these filters can help in achieving faster (structural) interpretation, for example in horizon interpretation.

We discuss one particular implementation of this principle in some detail: a simulated anisotropic diffusion process that diffuses (low-pass filters) the seismic amplitude. The diffusion tensor is computed from the local image structure (so that the diffusion is parallel to the reflections).

ACKNOWLEDGMENTS

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