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Seismic fault preserving diffusion

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Abstract

This paper focuses on the denoising and enhancing of 3-D reflection seismic data. We propose a pre-processing step based on a non-linear diffusion filtering leading to a better detection of seismic faults. The non-linear diffusion approaches are based on the definition of a partial differential equation that allows us to simplify the images without blurring relevant details or discontinuities. Computing the structure tensor which provides information on the local orientation of the geological layers, we propose to drive the diffusion along these layers using a new approach called SFPD (Seismic Fault Preserving Diffusion). In SFPD, the eigenvalues of the tensor are fixed according to a confidence measure that takes into account the regularity of the local seismic structure. Results on both synthesized and real 3-D blocks show the efficiency of the proposed approach.

Keywords: 3-D filtering; Anisotropic diffusion; Confidence measure; Seismic data; Structure tensor

1. Introduction

The acquisition and processing of reflection seismic data result in a 3-D seismic block of acoustic impedance interfaces. The interpretation of these data represents a delicate task. Geological patterns are often difficult to recognize for the expert.

This interpretation of seismic blocks mainly consists in reflector picking (i.e. identifying and recording the position of specific reflection events) and fault plane locating. To be able to pick the reflectors wherever they are located throughout the seismic volume, the interpreter must be able to determine the vertical displacement across faults, and above all, he must discriminate whether a discontinuity is due to noise or artefacts or is evidence of a fault (Fig. 1).

As manual interpretation is both costly and subjective, some authors have investigated the use of image processing to develop automatic approaches (Sønneland et al., 2000; Randen et al., 2001;Admasu and Toennies, 2004). The resulting automatic tools are useful for structural interpretation of seismic data, but these tools failed in tracking horizons across faults especially if the level of noise is high.

One way to improve the efficiency of both manual and automatic interpretation is to increase the quality of

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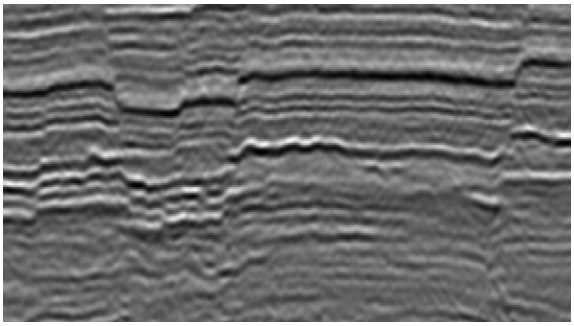

Fig. 1. A section of 3-D seismic data.

the 3-D seismic data by enhancing the structures to track as preserving the faults.

Among the different methods to achieve the denoising of 2D or 3-D data, a large number of approaches using non-linear diffusion techniques have been proposed in the recent years (Weickert, 1997). These techniques are based on the use of Partial Differential Equations (PDE).

The simplest diffusion process is the linear and isotropic diffusion that is equivalent to a convolution with a Gaussian kernel.

The similarity between such a convolution and the heat equation was proved by Koenderink (1984):

$$\frac{\partial U}{\partial t} = c\Delta U = \mathrm{div}(c\nabla U) \tag{1}$$

In this PDE, U represents the intensity function of the data; c is a constant which, together with the scale of observation t, governs the amount of isotropic smoothing. Setting $c=1$, Eq. (1) is equivalent to convolving the image with a Gaussian kernel of width $\sqrt{2t}$. div indicates the divergence operator.

Nevertheless, the application of this linear filter over an image produces undesirable results, such as edge and relevant details blurring.

To overcome these drawbacks Perona and Malik (1990) proposed the first non-linear filter by replacing the constant c with a decreasing function of the gradient, such as:

$$g(|\nabla U|) = \frac{1}{1+(|\nabla U|/K)^2} \tag{2}$$

where K is a diffusion threshold. The diffusion process is isotropic for contrast values under the threshold K; gradient vector norms higher than K are producing edge enhancing. Despite the quite convincing practical results, certain drawbacks remain unsolved: staircase effect (Whitaker and Pizer, 1993) or pinhole effect (Monteil and Beghdadi, 1999) are often associated with the Perona Malik process. In addition, in the strongly noised regions, the model may enhance the noise. Since the introduction of this first non-linear filter, related works attempted to improve it (Catte et al., 1992).

Weickert (1994, 1995) proposed two original models with tensor based diffusion functions. The purpose of a tensor based approach is to steer the smoothing process according to the directional information contained in the image structure. This anisotropic behaviour allows for adjusting the smoothing effects according to the direction.

The general model is written in PDE form, as:

$$\frac{\partial U}{\partial t} = \mathrm{div}(D\nabla U) \tag{3}$$

with some initial and reflecting boundary conditions.

In the Edge Enhancing Diffusion (EED) model, the matrix D depends continuously on the gradient of a Gaussian-smoothed version of the image (∇U_σ). The aim of this Gaussian regularization is to reduce the noise influence, having as result a robust descriptor of the image structure. For 2D application, the diffusion tensor D is constructed by defining the eigenvectors ($\overrightarrow{v_1}$) and ($\overrightarrow{v_2}$) according to $\overrightarrow{v_1} || \nabla U_\alpha$ and $\overrightarrow{v_2} \perp \nabla U_\alpha$(Weickert, 1994). The corresponding eigenvalues λ_1, λ_2 were chosen as:

$$\begin{cases} \lambda_1 = \begin{cases} 1, & \text{if } |\nabla U_\sigma| = 0 \\ 1-\exp\left(\dfrac{-1}{|\nabla U_\sigma|^2}\right), & \text{else} \end{cases} \\ \lambda_2 = 1 \end{cases} \tag{4}$$

In this manner, EED driven processes are smoothing always along edges ($\lambda_2=1$) and, in the direction of the gradient, the diffusion is weighted by parameter λ_1 according to the contrast level in that direction.

Besides the EED model which enhances edges, Weickert proposed also a model for enhancing flow-like patterns: the Coherence Enhancing Diffusion-CED- (Weickert, 1999). The structure tensor introduced in this model is a powerful tool for analyzing coherence structures. This tensor J_ρ is able to measure the gradient changes within the neighbourhood of any investigated point:

$$J_\rho(\nabla U_\sigma) = K_\rho^*(\nabla U_\sigma \otimes \nabla U_\sigma) \tag{5}$$

Each component of the resulted matrix of the tensor product ($\otimes$) is convolving with a Gaussian kernel (K_ρ) where $\rho \gg \sigma$. The eigenvectors of J_ρ represent the average orientation of the gradient vector ($\overrightarrow{v_1}$) and the