Geometrical model based method for fault detection

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Abstract—This paper describes on-going researches at the LASIS(1) to develop new approaches for fault detection of seismic 3D volume data. The paper provides an overview of method that we have recently developed in order to automatically restore the fault network.

Several coherency attributes have been proposed in the past ten years such as the so-called “coherence cube” or the multi-dip coherency estimate. In this paper, we extend the use of a time-vertical window to a steered one in order to provide directional coherency curves devoted to estimating fault direction. Furthermore, our method considers a model which assumes local linearity of fault geometry. Based on a directional search and continuity test, the proposed approach operates in three steps. First, for each dip-azimuth direction, a coherency estimate provides directional attribute curves. Secondly, in order to increase the selectivity of the detection, we introduce a non-linear steered filter applied on the attribute curves. The proposed filter uses a multi-segment criterion based on the linearity assumption. Thirdly, to improve the noise robustness of the detection, the attribute continuity is increased by means of a final accumulation step. This is obtained later by propagating the maximum value of the directional criterion in the local neighborhood of the surrounding voxel.

I. INTRODUCTION

Recent years have seen a rapid growth in the availability and confidence of the reflexive seismic data. Given the ease to elaborate geological models of underground information, there has been an increasing interest in interpreting these data. However, interpretation is a difficult and time consuming task depending on the complexity of the considered data. In order to have a better view of the searched structures, e.g. faults, channels or stratigraphic anomalies, the geologist makes use of other types of data called attributes. These salient data are obtained by processing the original seismic data. Weak or strong amplitudes presenting a relative spatial continuity bring out the structures to be detected. Developing a contrasted and selective attribute is a significant challenge. In this paper, we focus on the attributes providing fault detection.

Due to the fact that layers are broken by faults, the attributes proposed in the literature are based on measuring the loss of local coherence or by pointing out a local disorder in seismic signals. In the mid 90’s such an attribute was first proposed in the literature calculating the measure on post-stack data. In 1995, Bahorich’s work [1] led to the well-known coherence cube approach. Based on computing the cross correlation between three adjacent traces, the attribute presents amplitude continuities and allows a better observation of a number of major faults. The main drawback of this attribute is its noise sensitivity. In order to avoid this drawback, the approach proposed by Marfurt [5] generalizes the coherence cube approach by using a multi-trace support and mainly by performing an eigenvalue decomposition of the covariance matrix. In another extension [6] Marfurt proposed a dip azimuth search thus avoiding the problem of geological layer orientation. Randen [7] proposed a seismic signal feature, exploiting its spatial and temporal derivatives. He proposed measuring the gradient vector field disorder caused by the fault crossing.

So, most of the recent approaches share the use of a principal component analysis (PCA) in order to point out structural changes in the 3-D seismic data. The two main approaches are the coherence [5] and the gradient disorder [7]. It can be shown that these two approaches give equivalent responses but this demonstration is out of scope of this paper. In this paper, the gradient disorder measurement has been chosen. Without descriptively questioning the approaches, it is clear that theirs drawbacks are the incapacity of finding the orientation and spatial extension of the seismic fault. Using a vertical reading of the data, the computation process introduces many artifacts in its responses, such as the staircase effect or the dislocation caused by broken continuity.

Thus, this paper present a new method of processing a fault detection attribute. The method uses the 2-D (3-D respectively) geometrical modeling of the fault, supposed to have a local linear or planar extension, respectively. The approach consists mainly in searching for the strongest response of a directional attribute measuring the gradient disorder.

The paper is organized in four sections. Section II is a reminder of the fault detection method proposed in the literature. In the following section we present our approach. The proposed method is mainly based on a directional analysis, presented in the first part of paragraph III. Particularly, we describe the computation of an attribute of disorder, called directional coherence, along a variable analysis direction. Secondly, we introduce a directional filtering of the initial response. The purpose is to have better visibility and to reduce the sensitivity in the so called “deaf
zones” or chaos zones, and also in the sedimentary deposition zones. This step is similar to the directional thinning step proposed by Randen [7], but in our approach, the directional search is expressed as a function of a directional measure. The direction of the fault is contained in the directional coherence. Thirdly, the pertinence of the approach is improved in the final stage presented in the last part of paragraph III. The directional response regarded as a probability of presence or as a confidence measure is propagated by an accumulation process. At the end, these three steps form the global computation process of a new fault detection attribute [2].

II. OVERVIEW OF THE TENSOR METHOD

Let us define the seismic signal value \( p(x, y, t) \) of a 3-D spatio-temporal \( [x, y] \) position in the current data block.

The gradient disorder attribute aims to evaluate the local disorder described by the seismic data. In fact, the orientation and magnitude of the gradient vector field are used to detect the disorder. Layered seismic zones provide ordered fields, whereas for areas containing faults, the gradient vector field is corrupted.

By exploiting the structure tensor introduced by Bigün [3], the gradient disorder measure is provided taking into account the following matrix:

\[
T(s) = \begin{bmatrix}
D_x^2 & D_x D_y & D_x D_t \\
D_x D_y & D_y^2 & D_y D_t \\
D_x D_t & D_y D_t & D_t^2
\end{bmatrix}
\]

where the operator \( D \) denotes the spatial gradient components given by:

\[
\nabla (p(s)) = \begin{bmatrix} D_x & D_y & D_t \end{bmatrix}^T, \text{ where } D_x = \frac{\partial p(s)}{\partial x}.
\]

The gradient disorder attribute can be obtained by using the eigenvalue properties of the structure tensor. Explicitly, a strong variation of the eigenvalue magnitudes shows the inertial gap of spectral density projected respectively on the principal direction and the orthogonal one. The attribute is computed according to the dimensionality of the data:

2-D case: \( c(s) = \frac{\lambda_1 - \lambda_2}{\lambda_1 + \lambda_2} \),

3-D case:

- planar structure: \( c(s) = \frac{\lambda_1 - \lambda_2}{\lambda_1 + \lambda_2} \),

- linear structure: \( c(s) = \frac{\lambda_2 - \lambda_3}{\lambda_2 + \lambda_3} \).

In the case of the layered zones, only the principal eigenvalue of the gradient field is not equal to 0. The corresponding direction is orthogonal to the orientation of the layers and the attribute tends towards 1. Otherwise, in the multi-modal case or due to local noise, the attribute decreases proportionally to the directional disorder.

Figure 2 shows the coherence attribute for a selected part of the seismic data. The gradient vector field is disturbed when fault crossing a layered zone. We can observe the major drawback which is the staircase effect. The staircase effect is undesirable first because the continuity of the fault is destroyed and second because it corresponds to a false positioning of the fault, which increases with scale.

III. OVERVIEW OF THE TENSOR METHOD

Classical fault detection attributes have several drawbacks such as staircase effect, broken continuity, false localization and high noise sensitivity. These results clearly demonstrate the fact that the measure using a neighborhood of time-vertical traces is devoted to the seismic layer analysis and not to fault detection. Thus, our target is to design an additional process in order to increase the relevance of the fault model. We hypothesize that the fault is locally described by a line segment (respectively a plane patch) of maximal disorder. Taking into account this model, we propose a new method to compute the fault extraction attribute. This method operates in three steps. The first step deals with the calculation of the attribute curves, where we use steered version instead of time vertical traces. This enables us to adapt the traces to the fault orientation. Then we calculate, from those angular attribute curves, a directional criterion curve and search for the maximum magnitude. The maximum indicates the orientation of the fault. Finally, the third step creating the new fault attribute corresponds to a voting level providing a robust filter.

A. Attribute curve evaluation

As already stated the attribute curves are based on the gradient field disorder measure. For the purpose of fault characterization we project the disorder measure onto an orientation space. We respectively build a 1-D signature for the 2-D case and a 2-D one for the 3-D case. In order to obtain high orientation resolution, we use a moving analysis window fitted to the local geometric model of the fault. In the 2-D case, with the analysis window containing only one data vector, we sample the orientation space with \( \{ \theta_i; i = [1 : J] \} \) distributed evenly along the orientation axis, \( \theta \). While for the 3-D case we have a 2-D orientation space quantified by \( \{ \theta_i, \alpha_j; i = [1 : I], j = [1 : J] \} \). In the orientation signatures, which are the attribute curves, the local extremes represent the orientations of disorder alignments.

In order to provide a formal description of the measurement, let us consider \( \mathcal{D}(v, s) \) the Dirac directional operator having no zero values on the line defined by the normal vector \( v \), and \( \mathcal{D}_N(v, s) \) the same operator on a finite
support, corresponding to a symmetric $N$-length segment and centered at the site $s$. Using the latter, we can define an oriented windowed trace given by:

$$p_{v,N}(s) = p(s) \overrightarrow{N}(v,s) \text{ with } v = [-\sin(\theta) \cos(\theta)]^T$$

Following this definition, we can introduce the sub-tensor $T[v,s]$ as the tensor computed according to the spatio-temporal gradient associated to the oriented trace $p_{v,N}(s)$

$$T[v,s] = \begin{bmatrix} D_v^2 \overrightarrow{N}(v,s) & D_v D_s \overrightarrow{N}(v,s) & D_s D_v \overrightarrow{N}(v,s) \\
D_v D_s \overrightarrow{N}(v,s) & D_s^2 \overrightarrow{N}(v,s) & D_s D_v \overrightarrow{N}(v,s) \\
D_v D_s \overrightarrow{N}(v,s) & D_s D_v \overrightarrow{N}(v,s) & D_v^2 \overrightarrow{N}(v,s) \end{bmatrix}$$

with $c(v,s) = 1 - \frac{\lambda_2}{\lambda_1 + \lambda_2}$.

Considering the directional measurement, the detection procedure needs another processing step because a point from a fault attracts most other points in its neighborhood, due to the steerability of the measure. This undesired effect creates the so-called “butterflies” on the final attribute map. The “butterfly” dimension is strictly related to the length of the windowed steered trace. Searching for the maximum of that attribute curve means that we search for the direction of maximal gradient disorder. A point placed sufficiently close to a fault is characterized by a maximum disorder for an angle intersecting the fault.

B. Directional filtering

Searching for the maximum of the attribute curve is not sufficient. In order to avoid the “butterfly effect” and to reduce the scale effect we introduce a directional criterion based on these attribute curves.

We work on a small scale when evaluating the attribute curves and then mix the values of several small scale segments (plane patches in 3-D case) to propose a new directional criterion in order to enhance the detection selectivity (Fig. 2).

![Figure 1: Multi-segment (plane) support 2-D (3-D) case.](image)

Taking into account the middle points of each sub-segment or sub-plane, we propose a new angular criterion given by the following mixture:

$$\text{Crit}(v,s) = \prod_{j=1}^{k} c(v,s_j)$$

where:

- $\text{Crit}(v,s)$ - the angular criterion;
- $k$ - the number of sub-segments (plane patches);
- $c(v,s)$ - the angular attribute.

C. Directional filtering

To complete the approach and in order to increase the continuity of the new attribute, we develop the accumulation procedure in the final step.

The purpose of the accumulation process is to take into account the geometric expansion of the fault and to ensure the continuity of the final attribute, by developing interaction between the neighboring points.

The accumulation process starts by searching for the maximum of the criterion curves. This means that we want to find the most probable direction of the fault. Once we have found the maximum, the accumulation process adds the value to each point of the multi-zone line segment oriented according to the angle corresponding to the maxima of Crit$\{v,s\}$. Thus, at the end of the accumulation process, a point of the new attribute image has the following value:

$$v_{\text{max}} = \text{ArgMax}\text{Crit}(v,s)$$

$$\text{Acc}(s) = \sum_{p \in \Omega} \text{Crit}(v_{\text{max}}, p)$$

where:

- $\text{Acc}(s)$ - is the accumulated image, and also the final attribute image;
- $\Omega$ - the neighborhood influencing the current point. In the 2-D case $\Omega$ is a line segment oriented by $v_{\text{max}}$, and a plane for the 3-D case.

The methodology presented here was applied to the 3-D seismic volume corresponding to the Rosa oil field (Fig. 3). This field is characterized by a fault system crossing several chaotic areas and complex sedimentary features due to the presence of turbiditic channels. Our attribute (Fig. 3c) leads to an increased continuity of the fault responses and the results propose a less biased view of each of them.

IV. CONCLUSION

In this paper, we have presented a new algorithm for portraying faults from 3-D seismic data. Based on the well-known coherence measure, the proposed approach differs from the classical coherence cube technology by the use of a directional computational scheme constrained by a fault plane model. Consequently, an attractive characteristic of our new attribute is that it provides a convenient display of faults without other stratigraphic anomalies such as rivers, channels or reefs. The new algorithm takes advantage of the local linearity assumption of the fault geometry for filtering unstructured discontinuities and enhances the continuity of fault signatures. The response robustness is enhanced by introducing a directional filtering reducing, for instance, the false detections caused by the sedimentary depositions. The proposed approach significantly reduces the artifacts obtained with classical methods. Another advantage is the
absence of making any decision concerning the existence of the fault, as already proposed in the approach of Gibson [4]. The author suggests building the attribute with a predefined threshold on the coherence cube.

REFERENCES


Figure 2: (a) inline section of a fault; (b) Tensor approach proposed by Randen; (c) accumulated image based on the gradient field disorder attribute curves, $N = 21$, $L = 63$, $\theta_{\text{lim}} = 45^\circ$.

Figure 3: (a) Seismic amplitude time slice from Rosa field; (b) corresponding coherence attribute slice, $N = 21$; (c) corresponding directional attribute slice, $N = 19$, $K = 5$. 