Chapter 3

SEISMIC ATTRIBUTE-AIDED FAULT DETECTION IN PETROLEUM INDUSTRY: A REVIEW

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Abstract

In petroleum exploration and production, faults are of importance by controlling pathways of hydrocarbon migration and accumulation in the subsurface, and robust fault detection is one of the major tasks of geologic and geophysical interpretation from three-dimensional (3D) seismic data. Traditionally, faults are interpreted by manually picking on vertical/horizontal seismic sections with geologic consistence; however, such manual tool is time consuming and sensitive to the visibility and interpreters’ bias, especially for a large dataset with structural complexities. With the development of new signal processing and data visualization technologies, computer-aided semi-automatic/automatic fault extraction has been the focus of recent geophysical research on seismic fault detection with superiorities in both computational efficiency and result accuracy. Various methods have been developed and

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implemented in the petroleum industry; however, their results are often limited by the detection resolution and contaminated by non-fault artifacts that interfere with reliable structural interpretation. This paper provides a comparative analysis and comprehensive review of the existing fault detection methods, including manual picking and computer-aided automatic/semi-automatic extraction. A suite of algorithms for each method are tested regarding their computational efficiency and result accuracy by calibrating their results to the original seismic images for quality control. Finally, for addressing the limitations and problems observed in the existing techniques, innovative solutions are presented to further enhance the reliability of fault interpretation from seismic data.

Introduction

Fault detection from three-dimensional (3D) seismic data is essential for subsurface structure interpretation and reservoir characterization in petroleum exploration and production. Traditionally, faults are manually picked from vertical sections of seismic amplitude by an experienced interpreter. However, manual picking is time consuming, labor intensive, and moreover sensitive to interpreters’ bias, especially for large datasets with complex fracture networks. Then, in order to improve both interpretational efficiency and accuracy, geologists and geophysicists have made great efforts in developing algorithms for effective semi-automatic/automatic fault extraction from 3D seismic data with the aid of powerful computers and workstations (e.g., Pedersen et al., 2004; Tingdahl & de Rooij, 2005; Admasu et al., 2006; Hale, 2013; Wang and AlRegib, 2014b; Zhang et al., 2014). In general, these algorithms consist of three steps: first to generate a suite of seismic attributes (such as discontinuity) from the seismic dataset, in which faults are highlighted as lineaments; then to perform fault enhancement that further sharpens the imaging of seismic faults with the non-fault features suppressed or even removed, so that they could be easily differentiated by computer programs; finally to extract patches from the enhanced fault images by either an automatic detection algorithm with fault-related parameter configurations (such as fault size and orientation) or a semi-automatic detection algorithm with seeds pre-defined by an interpreter.

3D seismic surveying has been the most popular method for reservoir exploration and production since it was first applied in 1970s owing to its straightforward delineation of subsurface geologies by monitoring seismic wave propagation in three dimensions. In particular, faults are associated with abrupt lateral changes in seismic amplitude and/or waveform, and such observation allows geophysicists to highlight the faults by evaluating such changes in a qualitative/quantitative manner, denoted as discontinuity attribute. Seismic

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Seismic Attribute-Aided Fault Detection in Petroleum Industry

coherence is the first discontinuity attribute presented for detecting faults and stratigraphic features that uses a cross-correlation operator to estimate lateral waveform similarity (Bahorich and Farmer, 1995), whereas lateral variation of seismic amplitude was first estimated by applying the Sobel filter (Luo et al., 1996). The first-generation algorithms involve only three neighboring traces, making them highly sensitive to noises present in seismic data. The signal/noise ratio of the generated discontinuity images is improved by incorporating more traces into discontinuity analysis, such as the semblance presented by Marfurt et al. (1998), the eigenstructure-based coherence presented by Gersztenkorn and Marfurt (1999), the local structural entropy presented by Cohen and Coifman (2002), and the similarity presented by Tingdahl and de Rooij (2005). In general, all these algorithms are based on the assumption of seismic signals being zero mean, from which faults can be highlighted in an accurate manner. In most cases, however, mean of localized amplitude/waveform variation rarely is zero; thereby performing discontinuity detection on such data will undesirably weaken the contrast between discontinuities and continuous portions and decrease the detection resolution. The limitation is addressed by rescaling local amplitude before discontinuity attribute computation, so that the lateral resolution could be enhanced for subtle faults and fractures existing in seismic reflectors with nonzero-mean amplitude variation (Di and Gao, 2014). The discontinuity analysis greatly facilitates manual fault picking, and seismic faults especially those perpendicular to the beddings can be clearly recognized and picked by interpreters. However, when applying the generated discontinuity images to semi-automatic/automatic fault extraction, they are limited in both resolution and accuracy. First, due to noises in seismic data, discontinuity attributes highlight not only the true faults of interpretation interest, but also some artifacts with discernable waveform/amplitude variations that may be undesirably extracted as fault patches by computers. Second, for faults with a wide damaging zone, discontinuity attributes often highlight them as lineaments with a certain thickness, instead of thin lines, which adds to the difficulties for computers to determine the optimal location for extracting a one-pixel-thick patch that best represent such a thick faulting zone.

Then, fault enhancement is presented for improving the discontinuity resolution and moreover thinning the thick lineaments, and various approaches have been developed and applied to seismic fault detection (e.g., Pedersen et al., 2004; Cohen et al., 2006; Bag & Harit, 2011; Hale, 2013; Wang et al., 2014; Zhang et al., 2014). Among them, the ant tracking (Pedersen et al., 2004) and the lineament thinning (Hale, 2013) are considered most popular with wide applications in the industry. In particular, the former applies the principles of
swarm intelligence and describes the collective behavior of ants finding the shortest path between the nest and a food source by communicating via pheromone, a chemical substance that attracts other ants (Pedersen et al., 2004). However, while enhancing the faults in seismic data, such tracking also exaggerates artifacts with weak waveform/amplitude variations, such as processing effects, channel boundaries, and chaotic responses, all of which are magnified to the same level as the faults of interest and could be extracted as fault patches by mistake. Instead, the thinning approach proposed by Hale (2013) is capable of generating one-pixel-thick lineaments without exaggerating artificial lineaments by performing discrete scanning over both fault strike and dip to search for maximum waveform semblance. Correspondingly, the thinned lineaments are capable of accurately representing seismic faults and thus can be easily identified as patches by computers without causing ambiguities in determining fundamental fault properties (e.g., location, size, and orientation).

Manual picking of seismic objects, such as faults, horizons and salt domes, is limited by its efficiency and sensitivity to interpreter bias, especially for large seismic datasets with interpretational uncertainties; then semi-automatic/automatic extraction has been the research focus since 1990s. For example, Meldahl et al. (1999) presented a semi-automatic approach for detecting seismic chimneys by combining directive attributes and neural network, and such approach was later adapted to fault extraction from 3D seismic data by Tingdahl and de Rooij (2005). Gibson et al. (2005) and Zhang et al. (2014) proposed grouping fault points into the local planar patches and then merging these small patches into larger fault surfaces under certain geometric constraints. Admasu et al. (2006) proposed an autotracking method of fault line propagation from one section to another within the whole volume to obtain fault patches. Hale (2013) proposed a dynamic time warping algorithm to generate fault surfaces based on the boundary constraints derived from the thinned discontinuity images. Wang and AlRegib (2014a, b) introduced 3D Hough transform to detect potential fault planes in a seismic volume and the ideas of motion vectors in video coding and processing to extract fault surfaces. Unfortunately, all these algorithms are unable to simultaneously achieve both high resolution in extracting true faults and high accuracy in avoiding non-fault artifacts. The common result is either an aggressive case with high resolution (most/all true faults extracted) but low accuracy (many artifacts introduced), or a conservative one with high accuracy (few artifacts introduced) but low resolution (few true faults extracted). Therefore, semi-automatic/automatic fault extraction is still in the experimental phase for testing and not ready for practical implementation and application to industrial projects.
The purpose of this paper is to provide a comprehensive review for fault interpretation techniques from 3D seismic data presently used in the petroleum industry. The paper starts with a description of the seismic attributes that are most useful for fault delineation and interpretation; then fault detection is performed by both manual picking and semi-automatic/automatic extraction using a 3D seismic dataset from the North Sea that is rich in natural faults. Finally, the results are calibrated to the original seismic images for quality control, and future developments are proposed for overcoming the observed problems and leading to more robust computer-aided detection of seismic faults.

![Figure 1](image.png)

Figure 1. The 3D seismic dataset from the North Sea dominated by salt domes and salt-related faults.
Attribute Extraction

This section summarizes the major approaches implemented in the fault-detection algorithms that are capable of promoting the visibility of seismic faults, including data preconditioning, discontinuity analysis, and fault enhancement. To be consistent for comparative analysis, we use a 3D seismic volume from the North Sea (Figure 1) that is dominated by salt domes and associated faults. The dataset contains 600 inlines and 950 crosslines with the depth ranging from 1552 ms to 1848 ms at 4-ms interval, and all results are shown along the same vertical and horizontal sections for fair comparisons.

Post-stack amplitude is the most widely used seismic data in subsurface exploration. Figure 2 displays the horizontal slice of 1728 ms and the vertical slice of inline 425 in the dataset, with the black line indicating the location of the corresponding slice. From both slices, several faults are recognized as abrupt changes in the waveform patterns, especially for those perpendicular to the beddings. In contrast, the bedding-parallel faults are not well revealed in the amplitude images, and highlighting such fault usually requires the assistance with seismic attribute analysis, such as discontinuity.

![Figure 2](imageURL)

Figure 2. The horizontal slice of 1728 ms (left) and the vertical slice of inline 425 (right) of post-stack amplitude. Black line denotes the location of one in the other.
Data Preconditioning

Due to the noises existing in 3D seismic data, noise-suppression techniques, such as signal filtering and data smoothing, are often applied for data conditioning before interpretation, so that the features of interpretation interest could be shown more clearly whereas the noise-related artifacts could be effectively suppressed or even eliminated. Various filtering/smoothing algorithms have been introduced from other fields like image processing, and two most popular ones are median filter and edge-preserved smoothing.

Median Filter

Median filter is a nonlinear smoothing method that was first developed in image processing; and when applied to seismic data filtering, it works effectively for removing random noises and at the same time preserving seismic discontinuities. Such filter is easy for implementation by replacing the value at a sample with the median value of neighboring samples within a user-defined 2D or 3D analysis window. Figure 3 displays the corresponding horizontal slice of 1728 ms and the vertical slice of inline 425. Compared to the original post-stack amplitude (Figure 2), both images are cleaned after median filtering with the faults better highlighted, especially in the vertical section.

![Figure 3. The horizontal slice of 1728 ms (left) and the vertical slice of inline 425 (right) of median filtering. Black line denotes the location of one in the other.](image-url)
**Edge-Preserving Smoothing**

Edge-preserving smoothing is a derivation of the general running-average smoothing method and effectively resolves the conflict between noise suppression and edge degradation from the conventional statistical filters, such as the median filter. The principle of such method is to search for the most homogeneous fragment around each sample within a user-defined 2D or 3D window and assigns the average value of the fragment to that sample. The standard deviation is often selected for quantifying local homogeneity (Luo et al., 2002). However, such discrete searching increases the associated computational expense especially when the searching is in 3D and the window size is large. Figure 4 displays the corresponding horizontal slice of 1728ms and the vertical slice of inline 425, in which the noises are significantly suppressed and more importantly, the faults are enhanced with their planes delineated more clearly than those in Figure 3.

![Figure 4](image_url)

Figure 4. The horizontal slice of 1728 ms (left) and the vertical slice of inline 425 (right) of edge-preserving smoothing. Black line denotes the location of one in the other.

**Discontinuity Analysis**

Direct fault interpretation from seismic amplitude is limited in two major ways. The first limitation is its low resolution on highlighting faults that are parallel/subparallel to seismic reflections, especially when the dataset is contaminated by noises. Second, amplitude is applicable to only manual fault interpretation; when turning to semi-automatic/automatic fault extraction, such
information is not uniquely linked to faults although it could be well resolved by interpreters. Instead, computer-aided fault detection requires an edge-type display of seismic faults as input, in which only faults are highlighted whereas other features are strongly depressed or even removed. Both limitations are addressed by performing discontinuity analysis from seismic amplitude, which quantifies the lateral variations of seismic amplitude and/or waveform. There exists a suite of discontinuity attributes, and the major ones are selected as follows.

**Coherence**

Seismic coherence was the first discontinuity attribute presented for delineating faults and stratigraphic features, which uses a three-trace cross-correlation operator to measure the similarity between the localized waveform at a sample and those at its surrounding samples (Bahorich and Farmer, 1995). Let $s_0$ denote the waveform at the target sample, $s_x$ and $s_y$ the waveforms at its surrounding sample along the inline (x-) and crossline (y-) directions, respectively, then the coherence attribute $c_1$ is estimated as

$$c_1 = \frac{\sum_{k=1}^{K}(s_0(k) - \bar{s}_0)(s_x(k) - \bar{s}_x)}{\sqrt{\sum_{k=1}^{K}(s_0(k) - \bar{s}_0)^2 \cdot \sum_{k=1}^{N}(s_x(k) - \bar{s}_x)^2}} \cdot \frac{\sum_{k=1}^{K}(s_0(k) - \bar{s}_0)(s_y(k) - \bar{s}_y)}{\sqrt{\sum_{k=1}^{K}(s_0(k) - \bar{s}_0)^2 \cdot \sum_{k=1}^{N}(s_y(k) - \bar{s}_y)^2}}$$  \hspace{1cm} (1)

where $\bar{s}_0$, $\bar{s}_x$ and $\bar{s}_y$ denote the average of waveforms $s_0$, $s_x$ and $s_y$, respectively. $K$ denotes the size of vertical analysis window.

The visualization of seismic coherence often uses a black-gray-white color map, in which a fault is highlighted in black (low value) indicating significant waveform changes, whereas the continuous portion is in white (high value). Figure 5 displays the coherence images of the horizontal slice of 1728 ms and the vertical slice of inline 425, in which the faults are clearly detected especially those parallel to beddings (denoted by arrows).

**Sobel Filtering**

Sobel filter is a common edge detector used in the field of image processing, which effectively detects edges in an image by measuring the gradient of amplitude at each pixel. When applied to seismic data, the amplitude gradient $c_2$ is estimated as the square root of two gradients of seismic amplitude $u$ along inline (x-) and crossline (y-) directions (Luo et al., 1996),
In contrast to the coherence attribute, amplitude gradient highlights faults with high values, whereas the continuous portions have low amplitude gradient. For comparison, the color polarity for amplitude gradient is reversed in this paper, so that a fault is always associated with black whereas continuous structure is white. Figure 6 displays the amplitude-gradient images of the horizontal slice of 1728 ms and the vertical slice of inline 425, in which the faults are also clearly imaged in the way similar to the coherence attribute (Figure 5).

Figure 5. The horizontal slice of 1728 ms (left) and the vertical slice of inline 425 (right) of coherence.

Figure 6. The horizontal slice of 1728 ms (left) and the vertical slice of inline 425 (right) of Sobel filtering.

\[
c_2 = \sqrt{\left(\frac{\partial u}{\partial x}\right)^2 + \left(\frac{\partial u}{\partial y}\right)^2}
\] (2)
Semblance

The semblance attribute measures lateral changes in seismic amplitude by incorporating more traces to reduce the sensitivity to noise present in a seismic dataset (Marfurt et al., 1998). Let $u$ denote the amplitude within a lateral analysis window of $J$ samples and a vertical analysis window of $K$ samples, then the semblance $c_3$ is estimated as

$$
c_3 = \frac{\sum_{k=1}^{K} \left[ \sum_{j=1}^{J} u(j,k) \right]^2 + \left[ \sum_{j=1}^{J} u_H(j,k) \right]^2}{J \sum_{j=1}^{J} \sum_{k=1}^{K} [u^2(j,k) + u_H^2(j,k)]}
$$

(3)

where $u_H$ denotes the Hilbert transform or quadrature component of the real seismic amplitude $u$. The quadrature amplitude allows to obtain robust estimates of semblance even about the zero crossings of seismic reflection events (Marfurt et al., 1998).

Similar to the coherence attribute, faults are highlighted in black (low semblance) as amplitude variations within the defined analysis windows are assumed being zero mean, whereas the continuous portions are in white (high semblance) due to theoretically constant amplitude in the windows. Figure 7 displays the semblance images of the horizontal slice of 1728 ms and the vertical slice of inline 425, in which the faults are clearly imaged with higher resolution on the portions associated with weak waveform/amplitude variation (denoted by the black circle).

Figure 7. The horizontal slice of 1728 ms (left) and the vertical slice of inline 425 (right) of semblance.
Similarity

The similarity attribute integrates the waveform similarity and amplitude variation, and the three-trace similarity $c_4$ is estimated as (Tingdahl and de Rooij, 2005)

$$c_4 = \frac{1}{2} \left[ \frac{\sum_{k=1}^{K} [s_0(k) - s_x(k)]^2}{\sqrt{\sum_{k=1}^{K} s_0^2(k) + \sum_{k=1}^{K} s_x^2(k)}} + \frac{\sum_{k=1}^{K} [s_0(k) - s_y(k)]^2}{\sqrt{\sum_{k=1}^{K} s_0^2(k) + \sum_{k=1}^{K} s_y^2(k)}} \right]$$

(4)

where $s_0$ denotes the waveform at the target sample, $s_x$ and $s_y$ the waveforms at its surrounding sample along the inline (x-) and crossline (y-) directions, respectively. $K$ denotes the size of vertical analysis window.

By the similarity attribute, faults are highlighted with high values indicating significant changes in both waveform and amplitude, whereas low similarities are estimated in the continuous portions where little changes in waveform and amplitude are expected. Figure 8 displays the similarity images of the horizontal slice of 1728 ms and the vertical slice of inline 425, in which the faults are better imaged with higher resolution than the coherence, amplitude gradient, and semblance images (Figure 5-7).

![Figure 8. The horizontal slice of 1728 ms (left) and the vertical slice of inline 425 (right) of similarity.](image-url)
Canny Edge Detection

As the most effective detector in the field of image processing, the Canny edge detector was introduced to seismic data (Di and Gao, 2014); and more importantly, mean removal is proposed to enhance the resolution on features where amplitude variation is often of non-zero mean. For amplitude $u$ within a lateral analysis window of $J$ samples and a vertical analysis window of $K$ samples, the Canny edge detection $c_5$ is estimated as

$$c_5 = \frac{\sum_{k=1}^{K} \left[ \sum_{j=1}^{J} f_x(j) \tilde{u}(j,k) \right]^2 + \left[ \sum_{j=1}^{J} f_y(j) \tilde{u}(j,k) \right]^2 + \left[ \sum_{j=1}^{J} f_x(j) \tilde{u}_H(j,k) \right]^2 + \left[ \sum_{j=1}^{J} f_y(j) \tilde{u}_H(j,k) \right]^2}{\sum_{k=1}^{K} \sum_{j=1}^{J} \left[ f_x(j) \tilde{u}^2(j,k) + f_y(j) \tilde{u}^2(j,k) + f_x(j) \tilde{u}_H^2(j,k) + f_y(j) \tilde{u}_H^2(j,k) \right]}$$

(5)

where $\bar{u} = u - \bar{u}$ and $\bar{u}_H = u_H - \bar{u}_H$ denote the real amplitude $u$ and quadrature amplitude $u_H$ after mean removal, respectively. $f_x = -\frac{x}{\sigma^2} G$ and $f_y = -\frac{y}{\sigma^2} G$ denote the Canny edge detector in inline ($x$-) and crossline ($y$-) directions, respectively. $G = \exp\left(-\frac{x^2+y^2}{\sigma^2}\right)$ is the Gaussian filter, in which $\sigma$ is the standard deviation.

Figure 9 displays the Canny detection of the horizontal slice of 1728 ms and the vertical slice of inline 425, in which an enhanced resolution is observed for faults especially in the areas with weak amplitude variation (denoted by the black circle).

![Canny detection image](image_url)
Fault Enhancement

Even though discontinuity analysis helps identify seismic-scale faults and facilitates manual fault picking, interpretation ambiguities still exist when it is used for extracting fault patches by computers, for two major reasons. First, value of discontinuity attributes often varies laterally along a fault, which may segment the corresponding lineament into several separate parts (as shown in Figure 5-9) and thereby adds the difficulties for computers to continuously pick the fault as a whole patch. Second and more importantly, lineaments in discontinuity maps are often associated with a thickness of several pixels, especially for major faults with wide damaging zones, which adds the difficulties for computers to uniquely extract a patch that best represents fault geometry. Then fault enhancement techniques are developed to resolve both limitations, and two most popular ones are ant tracking and lineament thinning.

Ant Tracking

The ant-tracking is based on the principles of swarm intelligence and describes the collective behavior of ants finding the shortest path between the nest and a food source by communicating via pheromone, a chemical substance that attracts other ants (Pedersen et al., 2004). Figure 10 illustrates how ant tracking works with two ants starting at the same time from the nest. The ant choosing the shorter path will return back to the nest before the ant choosing the longer path, and the shorter path will be marked with more pheromone than the longer path, which attracts the next ant more likely to choose the shorter path.

When applied to seismic fault enhancement, a large number of artificial ants move along what appears to be a fault surface, emit electronic pheromone, and make decisions based on their pre-coded behavior and the pheromone along the surface. Such tracking is terminated at samples where there is no surface, only unstructured noises, or where there is a surface which does not fulfill the user-defined conditions for a fault (e.g., size, orientation). The benefits of the ant tracking are that, faults of interest could be traced by many ants at different samples and hence be strongly marked by pheromone, whereas noise and surfaces unlikely to be faults should be unmarked or weakly marked and hence be removed by thresholding.

Figure 11 displays the ant-tracking of the horizontal slice of 1728 ms and the vertical slice of inline 425. Note that the faults are highlighted more continuous and sharper (one-pixel thick). However, one major limitation of the ant tracking is the undesired overestimates of artifacts and subtle faults with small throws, which
are exaggerated to the same level as the major ones (denoted by the black circle). Such exaggeration could be well avoided in manual fault picking by an experienced interpreter, but runs the risk of extracting non-fault features as patches by semi-automatic/automatic algorithms.

Figure 10. The sketch map of ant tracking (from Pedersen et al., 2004).

Figure 11. The horizontal slice of 1728 ms (left) and the vertical slice of inline 425 (right) of ant tracking.

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Lineament Thinning

The lineament thinning works by searching for the one-pixel-thick fault surface based on the discontinuity magnitude, so that the contrast between major faults and subtle ones is well preserved without exaggerating non-fault artifacts. Various algorithms have been developed (e.g., Cohen et al., 2006; Bag & Harit, 2011; Hale, 2013; Zhang et al., 2014a), and the scanning one by Hale (2013) is considered most useful in generating the thinned fault surfaces without generating undesired bifurcation branches in the presence of noises and complex boundaries.

At each sample, the scanning algorithm first defines suitable sampling intervals of possible fault strike $\phi$ and dip $\theta$ that avoid undersampling. Then for each orientation $(\phi, \theta)$, when the associated discontinuity value exceeds the maximum one stored at the sample, it is updated by the new value and also the corresponding strike $\phi$ and dip $\theta$ are saved. When the scanning completes, the results are images of thinned discontinuity attributes and corresponding fault strikes and dips (Hale, 2013).

Figure 12 displays the lineament thinning images of the horizontal slice of 1728 ms and the vertical slice of inline 425. It is clear that, the faults are represented by thin lineaments for interpretation, and meanwhile the artifacts and subtle lineaments in the weakly-deformed areas (denoted by the black circle) are ignored in the thinning process. Compared to the ant-tracking map (Figure 11), the thinned image serves as a better input for the semi-automatic/automatic fault patch extraction.

![Figure 12](image_url)

Figure 12. The horizontal slice of 1728 ms (left) and the vertical slice of inline 425 (right) of lineament thinning.

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Fault Mapping

Manual Fault Picking

Traditionally, faults are interpreted by manual picking on horizontal and vertical sections of seismic amplitude, and the accuracy of manual interpretation strongly relies on the interpreter’s insight and experience and conceptual understanding of the structural geology of sedimentary basins. With the recent developments in seismic attribute analysis and multi-attribute visualization, discontinuity and/or fault enhancement attributes are now often incorporated into fault interpretation by co-rendering them with the original amplitude, which helps interpreters better identify and pick the faults that are not easily discernable from amplitude due to weak waveform and/or amplitude variations. Take the North Sea dataset for example (Figure 13), manual picking is performed on a vertical section of seismic amplitude (left) and terminates in the bottom area where amplitude variation is invisible. However, when the corresponding lineament thinning is overlaid over the amplitude (right), the improved visualization allows us to continue picking the fault towards the bottom part of the vertical section, leading to more reliable interpretation of the target fault.

Figure 13. Manual fault interpretation (light blue) from post-stack amplitude.
Semi-Automatic Fault Extraction

Semi-automatic object detection has been successful in detecting various types of seismic features, including gas chimneys and faults. The semi-automatic fault detection often consists of three steps. First, the seismic data is scanned and a set of seismic attributes are calculated to clearly highlight faults and meanwhile reduce non-fault features. Next, faults are manually picked as seeds on a few sections of seismic amplitude and/or attributes. Finally, the manual picking is learned by a computer program and automatically extended to the entire cube, generating 3D patches throughout the whole volume.

One example is the semi-automatic detection using 3D Hough transform (Wang & AlRegib, 2014b). In particular, the likely fault points are highlighted in seismic data by thresholding the corresponding discontinuity volumes. Then 3D Hough transform is applied to detect the most-likely fault planes in seismic volumes (Figure 14). Finally, after filtering the noisy planes, the weighted plane fitting method is used to extract the smoothed fault surfaces from the remaining fault planes. Figure 15 displays the faults detected in two inline sections using the semi-automatic method, demonstrating its capability of extracting patches that fit the true faults.
Automatic Fault Extraction

Compared to the manual picking and semi-automatic extraction, the method of automatic seismic object detection avoids manual picking that is time-consuming and sensitive to interpretational bias, and thus is superior in both efficiency and accuracy. The automatic fault detection also consists of three steps. First, the seismic dataset is preconditioned by filtering and/or smoothing if necessary, and discontinuity attributes are generated from the amplitude volume, which could be these mentioned above or other derivations. Then the discontinuities are thinned to be one-pixel thick by applying the fault-enhancement approaches, and the thinned lineaments allow computers to uniquely quantify the fundamental properties about a fault, such as its location, geometry and size. Finally, fault patches are extracted from the thinned lineaments, each of which represents a fault in the subsurface.

In practice, due to its sensitivity to noises present in seismic data, automatic extraction often requires complicated parameterization/optimization, among which minimum patch size and confidence level are of most importance. In particular, the minimum patch size helps eliminate small faults without interpretation interest, and a larger size is used when only the major ones are the targets of fault interpretation. The confidence level controls the sensitivity to noises and/or artificial lineaments, and a high level helps avoid extracting non-fault artifacts; however, it runs the risk of missing the true faults. Figure 16 displays the fault patches extracted from the North Sea dataset using high and low
confident levels, respectively. It is clear that some small patches are not shown in
the result using conservative parameters (left), part of which are artifacts but the
rests may represent true faults. Therefore, even for automatic fault extraction,
isights from an experienced geologist/geophysicist are always needed to resolve
the conflict between high resolution and low accuracy.

Figure 16. Automatic fault detection from high (left) and low (right) confidence level.

Fault Map Quality Control

The results from semi-automatic/automatic fault detection are often calibrated to
the sections of amplitude and/or discontinuity attributes for quality control, such
as validating the patch geometry and size in regular seismic images. Figure 17 and
Figure 18 display the fault patches attached to the horizontal slice of 1728ms and
the vertical slice of inline 320, respectively. In general, patches are successfully
extracted for the major faults, and their geometry follows the actual fault
geometry with high confidence. However, two major limitations are observed.
First, as shown in Figure 17, a large fault is represented as several small patches
instead of a large one as expected (denoted by the red circle), which could be
misleading in reservoir structure interpretation and fault-network modeling.
Second, as shown in Figure 18, detection of a fault often terminates before
reaching the fault edges where the feature weakens to a lower level beyond the
resolution of semi-automatic/automatic extraction. Therefore, the extracted patch
is too small to be true, compared to its actual size and based on the interpretational
experience. Both limitations could be addressed by adjusting the parameter
settings according to the target fault, such as adding seed pickings in the areas
where the patches stop growing for semi-automatic extraction and lowering the
confidence level for automatic extraction; however, this may create new problems.
for picking the other faults in different orientations, decreasing the productivity and reliability for automatic fault extraction. Therefore, the automatic fault detection is still in the phase of experimental testing and not ready for reliable applications to industrial projects.

Figure 17. Fault patches calibrated to the horizontal slice of 1728 ms of lineament thinning.

**Future Work**

Discontinuity analysis is a fundamental process for fault enhancement and the associated patch extraction. A discontinuity attribute would help reveal and detect faults. However, existing discontinuity attributes are limited to seismic-scale faults and fractures. Beyond the discontinuity attribute, seismic geometric attributes, such as curvature and flexure (Gao, 2013; Gao and Di, 2015), can add to detect and characterize faults and fractures that fall below the seismic resolution (Di and Gao, 2016).

Fault enhancement methods, such as the lineament thinning algorithm, provides fault trace with one-pixel width, which could be implemented for
improving the existing semi-automatic/automatic algorithms or developing new ones to address the conflict between detection accuracy and artifact. Take the fault autotracking algorithm by Admasu et al. (2006) for example, the thinned fault traces could greatly facilitate fault propagation, leading to enhanced fault patches in 3D space.

![Fault patches calibrated to the vertical slice of inline 320 of post-stack amplitude.](image)

Figure 18. Fault patches calibrated to the vertical slice of inline 320 of post-stack amplitude.

Last, structure rules should always be honored when developing any geophysical algorithms for fault detection, so that the results are geologically valid. For example, a fault trace should not have abrupt bending, and thus fault patch extraction should stop where fault orientation changes dramatically. Due to the heterogeneity in finite strain along a major fault in 3D space, displacement along the fault often varies significantly, and it is common that part of it may fall below the detection criteria, leading to segmented and discontinuous fault patches. Therefore, a robust fault detection algorithm should be capable of delineating faults at various scales, identifying portions of weak faulting, and finding the associated fault gaps and tip lines in the fault propagation process.
Conclusion

In petroleum industry, there are many algorithms for fault detection from 3D seismic data. This study compares a suite of algorithms that are most helpful and applicable to discontinuity attribute analysis, fault enhancement, and automatic fault patch extraction. In general, these methods are capable of highlighting faults associated with apparent waveform/amplitude variations and extracting the corresponding fault surfaces with a fair resolution and accuracy. Problems still exist, particularly with splitting a larger fault into several small patches and detecting fault boundaries. Further efforts are needed for resolving the problems for improved fault detection from 3D seismic data.

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References


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### Biographical Sketches

**Haibin Di**

**Affiliation:** Formerly Department of Geology and Geography, West Virginia University, Morgantown, West Virginia, US; presently Center for Energy and Geo Processing (CeGP), Georgia Institute of Technology, Atlanta, Georgia, US

**Research and Professional Experience**

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<tr>
<th>Date</th>
<th>Position</th>
<th>Organization</th>
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<tr>
<td>01/2016 – 05/2016</td>
<td>Adjunct instructor</td>
<td>West Virginia Wesleyan College, US</td>
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<tr>
<td>05/2015-08/2015</td>
<td>Earth science intern</td>
<td>Chevron Energy Technology Company, US</td>
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<td>05/2014 – 08/2014</td>
<td>Geophysical intern</td>
<td>PetroTechnical Services (Schlumberger), US</td>
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<td>05/2013 – 08/2013</td>
<td>Geoscience intern</td>
<td>4GB Earth Sciences, US</td>
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Publications Last Three Years

Journal Publications (9)

- Di, H., and D. Gao, 2015, Volumetric extraction of most positive/negative curvature and flexure attributes for improved fracture characterization from 3D seismic data: Geophysical Prospecting, doi: 10.1111/1365-2478.12350.

Conference Presentations (8)


**Dengliang Gao**

**Affiliation:** Department of Geology and Geography, West Virginia University, Morgantown, West Virginia, US

**Research and Professional Experience**

<table>
<thead>
<tr>
<th>Date Range</th>
<th>Position</th>
<th>Institution/Company</th>
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<tr>
<td>08/2015– Present</td>
<td>Professor</td>
<td>West Virginia University, US</td>
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<tr>
<td>08/2009-08/2015</td>
<td>Associate Professor</td>
<td>West Virginia University, US</td>
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<tr>
<td>04/2008 – 03/2009</td>
<td>Staff Geophysicist</td>
<td>Chevron Energy Technology Company, USA</td>
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<td>05/1998 – 04/2008</td>
<td>Senior Geologist</td>
<td>Marathon Oil Company, US</td>
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<td>05/1997 – 05/1998</td>
<td>Post Doc Fellow</td>
<td>Exxon Production Research Company, USA</td>
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**Complimentary Contributor Copy**
Publications Last Three Years:


