Patch-level MLP classification for improved fault detection
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Summary
Fault detection and interpretation has been one of the routine tools used for subsurface structure mapping and reservoir characterization from three-dimensional (3D) seismic data. With the recent developments in machine learning and big data analysis, this study proposes an innovative method for efficient seismic fault detection based on semi-supervised classification of multiple attribute patches through the popular multi-layer perceptron (MLP) technique. Such method consists with five components: (a) attribute selection, (b) training sample labelling, (c) attribute patch retrieval, (d) MLP model training, and (e) volumetric processing. Compared to the traditional fault-detection schemes, the proposed one is superior in three aspects. First, the MLP classifier is capable of integrating as many attributes as specified by seismic interpreters, so that the seismic features are mapped and differentiated in a high-dimensional attribute domain. Second, the artificial intelligence makes it possible for optimizing the contributions from all input attributes to achieve best detection, so that the negative effects from using a less useful or “wrong” attribute are minimized. Third, the use of attribute patches incorporates local seismic patterns into training an optimal classifier, so that the random noises and/or artifacts of distinct patterns are efficiently excluded from the detection. The added values of the proposed method are verified through applications to the 3D seismic dataset over the Great South Basin (GSB) in New Zealand, where the subsurface structure is dominated by polygonal faults of varying sizes and orientations. The results demonstrate not only good match between the detected lineaments and the original seismic faults, but also great potential of the new workflow for assisting the existing fault interpretation tools, e.g. seeded picking and automatic extraction, to facilitate structural framework modeling in the exploration areas rich of faults and fractures.

Introduction
Faults and fractures are important subsurface structures of significant geologic implications for hydrocarbon accumulation and migration in a petroleum reservoir, and the presence of a fault can be visually recognized as a lineament/plane of abrupt variations of the signals in a three-dimensional (3D) reflection seismic dataset. However, fault interpretation is a time-consuming and labor-intensive process, especially for an exploration area of complex faults and complicated faulting histories. In the past decades, great efforts have been devoted into computer-aided fault interpretation by developing new attributes and methods/algorithms to help detect, depict, and extract the faults of interpretational interest from the surrounding non-faulting features.

Specifically, from the perspective of seismic attribute analysis, both edge detection and reflector geometry estimation are applicable to the problem of fault mapping from 3D seismic data, considering the lateral changes in seismic signals across a fault, including both reflection waveform/amplitude and event depth/two-way travelling time. The seismic edge detection was first presented as the coherence attribute by estimating the cross-correlation of two adjacent seismic traces to highlight the faults and stratigraphic features from a seismic cube (Bahorich and Farmer, 1995). Since then, substantial efforts have been devoted for improving such attribute as well as its variations in terms of detection resolution and noise robustness (e.g., Luo et al., 1996; Marfurt et al., 1998; Gerstenkorn and Marfurt, 1999; van Bemmel and Pepper, 2000; Cohen and Coilman, 2002; Tingdahl and de Rooij, 2005; Di and Gao, 2014a, Wang et al., 2016). A comprehensive summary of the edge-detection attributes can be found in Chopra (2002) and Kington (2015). However, the conventional seismic edge-detection is limited in its detection resolution for small-scale faults and fractures beyond the seismic scale and moreover offers no physical link for predicting the fundamental fracture properties (e.g., intensity, orientation, and sense of displacement) either quantitatively or qualitatively (Gao, 2013). Then the seismic geometric attributes are developed for more robust fault detection and fracture characterization by quantifying the lateral variations of the geometry of seismic reflectors, including the second-order curvature (Roberts, 2001; Al-Dossary and Marfurt, 2006) and the third-order flexure attributes (Di and Gao, 2014b; Yu, 2014; Gao and Di, 2015; Di and Gao, 2016; Qi et al., 2017). Comprehensive summaries of the curvature and flexure analysis can be found in Roberts (2001) and Di and Gao (2017), respectively.

From the perspective of fault interpretation methods, the manual picking is considered most reliable if performed by an experienced interpreter. However, it is limited by the interpretation efficiency especially for a large seismic dataset with complicated deformation history (e.g., folding and faulting). Correspondingly, the computer-aided fault interpretation becomes the research focus with the progress in computer graphics and image processing since 2000, and various methods/algorithms have been developed for refining the edge-detection attributes and interpreting fault surfaces (e.g., Pedersen et al., 2002; Barnes, 2006; Admasu et al., 2006; Hale, 2013; Zhang et al., 2014; Machado et al.,
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In this paper, we propose an innovative workflow for improving fault detection by patch-based multi-attribute MLP classification, which involves five components. After illustrating the workflow of the proposed method in details, we demonstrate its added values through applications to the 3D seismic dataset over the Great South Basin (GSB) in New Zealand, where polygonal faults of varying sizes and orientations dominate the subsurface structures.

Methodology

The proposed workflow for seismic fault detection via patch-based multi-attribute MLP classification is illustrated in Figure 1. It consists of five steps: (a) attribute selection, (b) training sample labelling, (c) attribute patch retrieval, (d) optimal MLP training, and (d) volumetric processing. For efficient evaluation of the proposed workflow, we use a small subset of the 3D seismic dataset (484 inlines by 501 crosslines by 76 samples per trace) over the Great South Basin (GSB) in New Zealand, where the subsurface structure is dominated by polygonal faulting of varying sizes and orientations.

A. Attribute selection

Attribute selection is considered as the key to successful multi-attribute based seismic feature classification, such as facies analysis (Zhao et al., 2015). For the purpose of fault interpretation in this study, we determine an attribute by whether the faults can be visually differentiated from the surrounding non-faulting features (such as horizons) in the corresponding attribute maps. Among all possible seismic attributes, we select and calculate fourteen attributes from the amplitude volume, including 4 geometric attributes, 6 edge detection attributes, and 4 texture attributes (Di et al., 2017).

For example, Pedersen et al. (2002) introduced the concept of ant colony optimization from computer science and developed an ant-tracking algorithm for sharpening the lineaments in a variance volume. AlBinhassan and Marfurt (2003) applied the 2D Hough transform for enhancing the fault lines on time slices, and later Wang and AlRegib (2014) extended it to 3D space for fault surface extraction from a semblance volume. Barnes (2006) performed eigenvector analysis to a coherence volume and designed a discontinuity filter of three components for imaging the steeply-dipping faults. Hale (2013) developed a discrete-scanning algorithm over dips and strikes for lineament thinning from a semblance volume and a dynamic time wrapping algorithm to generate fault surfaces based on the boundary constraints from the thinned semblance volume. Zhang et al. (2014) first applied a biometric algorithm to the coherence attribute for fault skeletonization and then grouped discrete fault points into one fault patch under local planar constraints. Wang et al. (2014) borrowed the ideas of motion vectors in video coding and processing to assist seismic fault extraction. Machado et al. (2016) performed volumetric fault imaging by applying the directional Laplacian of a Gaussian filter to coherence anomalies along reflector dip and azimuth.

If examined from the perspective of their inputs, all these methods utilize only a single edge-detection attribute (e.g., semblance, coherence, and variance), implying their full dependency on the attribute quality. In geology, however, some non-fault features (e.g., salt domes and stratigraphic channels), coherent noises (e.g., acquisition footprints), and processing artifacts are often detectable by a certain edge-detection algorithm and correspondingly would disturb the interpretation of actual faults if such an attribute is feed into computer-aided fault interpretation (Barnes, 2006). The risk can be reduced by integrating multiple seismic attributes of distinct operators, such as coherence and curvature. One simple approach is through an visualization of several attributes at a time, such as the co-rendering of three attributes in the red-green-blue (RGB) or hue-saturation-value (HSV) color space (e.g., Partyka et al., 1999; Stark, 2006; Laake, 2013). But such visualization is limited to the capture and parse more than four attributes. An alternative approach is to integrate multiple attribute through artificial intelligence, such as the support vector machine (SVM) (Di et al., 2017), multi-layer perceptron (MLP) (Tingdahl and de Rooij, 2005; Zheng et al., 2014), and the convolutional neural network (CNN) (Huang et al., 2017). However, such multi-attribute analysis is often simply based on the attribute values at each seismic sample, but ignores the local seismic patterns, causing its limited capability of differentiating seismic noises from the actual faults when they share similar attribute values but are distinct from the perspective of reflection patterns.

![Workflow Diagram](http://library.seg.org/)

Figure 1: The workflow chart of the proposed patch-level multi-attribute based fault detection from 3D seismic data using the multi-layer perceptron (MLP).

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B. Training sample labelling
Due to the lack of common training datasets in the field of seismic interpretation, we prepare the training samples used in this work by manually labelling the faults observed in three vertical section of crossline #2790, #2800, and #2810, which provides us with about 20,000 fault labels and 350,000 non-fault labels.

C. Attribute patch retrieval
The major improvement of the proposed workflow over the traditional ones is to retrieve attribute patches centered at every training sample, so that the MLP algorithm learns the local seismic patterns, instead of simply the attribute values at the central samples. The image patch used in this work is 9 inlines by 5 samples.

D. Optimal MLP training
The MLP is a class of feedforward artificial neural network consisting of at least three layers. Figure 2 illustrates the typical MLP architecture used for seismic feature classification, such as gas chimney, facies analysis, and fault detection. In particular, the input layer contains m neurons, each of which represents one of the selected seismic attributes. The output layer has 2 neurons: True and False, which represents fault and non-fault for the specific purpose of fault detection in this paper. The MLP network used in this study has q=3 hidden layers and p=32 neurons in each layer.

E. Volumetric processing
After verifying the accuracy of the built MLP classifier, it is then applied to the entire seismic survey for volumetric processing, which yields a fault volume, in which the potential faults are highlighted in value 1.0. Figure 3 demonstrates the 3D view of the generated fault volumes (in black), overlaying the original seismic amplitude (in blue-white-red). It is clear that the proposed method helps detect the faults in an accurate way.

Result analysis
For further analyzing the accuracy of fault detection by the proposed method, we clip the generated fault volume (Figure 3) into various sections and overlay them on the original seismic amplitude. First, Figure 4 demonstrates the results in the time section at 1132 ms, which clearly depicts the polygonal faulting as documented in this area.

Then it is clipped to four randomly-selected vertical sections, including inline #1791, inline #2011, crossline #2600, and crossline #3000 (Figure 5). Note that none of them were used in the training process, thus the faults in them are unknown to the trained MLP classifier. The good match between the detected fault lineaments and the original

Figure 2: The diagram for illustrating the architecture of the multi-attribute based MLP network from 3D seismic data. m attributes are retrieved at each of the n training samples that provides n neurons of the input layer, and the output layer consists of two labels, fault and non-fault. The input output layers are connected by q hidden layers, each of which contains p neurons. Such connection is optimized by adjusting the activities of all neurons, also known as weight w.

Figure 3: The 3D view of the generated fault volume (in black) in the GSB dataset using the proposed patch-level multi-attribute MLP classification, overlaying the original seismic amplitude (in blue-white-red).
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seismic images indicates the capability of the proposed method in effectively learning and identifying the target structures from a seismic volume.

Finally, we compare the results of the proposed patch-level classification and the traditional sample-level classification in Figure 6. It is clear that the use of attribute patches significantly improves the noise robustness of the MLP classification, particularly in the zones of weak reflection, so that the generated fault volume is clean with less false positive (denoted by circle).

Conclusions

This study has presented an innovative method for improved fault interpretation via patch-based multi-attribute classification using the popular multi-layer perceptron (MLP) algorithm. Such workflow is superior over the traditional ones in two aspects. First, it is capable of integrating as many attributes as specified by an experienced interpreter while traditional approaches (e.g., RGB co-rendering and cross plotting) limit their input to no more than four attributes. Second, the use of attribute patches into MLP training ensures that the machine learning takes into account local seismic patterns and thus is capable of learning and identifying the target seismic features in a more accurate manner, particularly in the presence of seismic noises and processing artifacts with distinct patterns.

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