Seismic Fault Detection from Post-Stack Amplitude by Convolutional Neural Networks

H. Di (Georgia Institute Of Technology), Z. Wang (Georgia Institute Of Technology), G. AlRegib* (Georgia Institute Of Technology)

Summary

Fault detection is one of the major tasks of subsurface interpretation and reservoir characterization from 3D seismic surveying. However, with the growing of seismic data in both its size and resolution, the efficiency of interpreting seismic faults increasingly relies on the development of powerful computational interpretation tools that are capable of mimicking an experienced interpreter’s intelligence. In recent years, the convolutional neural network (CNN) has been successful for image/video processing in various disciplines and is attracting more and more attentions from the petroleum industry. This study implements the popular CNN for the purpose of seismic fault detection, which is superior in two ways compared to the traditional sample-based multi-attribute classification schemes: (a) pattern-based, and (b) attribute-free. The added values of such CNN-based fault detection are demonstrated through applications to the fault-rich GSB dataset from New Zealand. The good match between the generated fault volume and the original seismic images not only verifies the capability of the CNN tool in assisting seismic fault interpretation, but also indicates greater potential for implementing more advanced machine learning techniques (e.g., FCN) into analyzing and interpreting seismic signals.
Introduction

Faults are important subsurface structures of great 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 three-dimensional (3D) reflection seismic signals. However, fault interpretation is a time-consuming and lab-intensive process, especially for an exploration area of vast 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 greatly applicable to the problem of fault mapping from 3D seismic data, owing to the lateral changes in seismic reflection waveform/amplitude and event depth/two-way travelling time across a fault. Such attributes include coherence (Bahorich and Farmer, 1995), semblance (Marfurt et al., 1998), similarity (Tingdahl and de Rooij, 2005), curvature (Roberts, 2001), and flexure (Di and Gao, 2017), and more derivatives (e.g., Luo et al., 1996; Gersztenkorn and Marfurt, 1999; Cohen and Coifman, 2002; Di and Gao, 2014; Wang et al., 2016; Qi and Marfurt, 2017). From the perspective of fault interpretation methods, the (semi-)automatic fault interpretation becomes the research focus in the past decades with the progress in computer graphics and image processing (e.g., Pedersen et al., 2002; Admasu et al., 2006; Hale, 2013; Machado et al. 2016). However, such methods utilize and parse only a limited number of attributes at a time, which runs the risk of introducing artifacts or misinterpretations if these attributes cannot well differentiate the faults from the surrounding non-faulting features. The most recent emerging of artificial intelligence provides geoscientists with more tools for integrating multiple attribute into seismic fault interpretation, including the multi-layer perceptron (MLP) (Tingdahl and de Rooij, 2005; Zheng et al., 2014), support vector machine (SVM) (Di et al., 2017), and convolutional neural network (CNN) (Huang et al., 2017). However, the accuracy of the multi-attribute based classification workflow greatly depends on an experienced interpreter in selecting a set of seismic attributes capable of distinguishing faults and the rest geologic features (e.g., Barnes and Laughlin, 2002; Zhao et al., 2015). Considering the complexities of subsurface geology and the presence of seismic noises, most seismic attributes fail to serve such purpose well. More importantly, the process of attribute selection need to be repeated from one seismic dataset to another. A simple hard-copy would undesirably fail due to the varying subsurface geology and the associated seismic expressions from area to area.

In this paper, we propose a new method for attribute-free fault detection by implementing the emerging CNN technique, which is superior in two aspects over the traditional multi-attribute based techniques. First, the CNN network defines, learns, and classifies the faults based on local seismic reflection patterns, so that the seismic noises and processing artifacts of distinct patterns can be effectively identified and excluded. Second and more importantly, the CNN network builds the mapping relationship between the seismic signals and the faults using the original seismic amplitude, instead of manually selected seismic attributes, so that the entire process requires less from an interpreters and is applicable to vast datasets without repeated efforts in attribute selection. The added values of the proposed workflow is demonstrated through applications to the 3D seismic dataset over the fault-rich Great South Basin (GSB) in New Zealand.

Methodology

The proposed workflow is shown in Figure 1, which consists of three components as below. As the testing dataset, we use a subset (484 inlines x 501 crosslines x 151 samples per trace) of the 3D GSB data that is featured with polygonal faults.

A. Training image preparation. For the supervised CNN classification in this study, we prepare the training images in three steps. First, the faults in three vertical sections, including crossline #2700, #2800, and #2900, are manually interpreted. Then, the 3 labelled crossline sections are discretized to provide us with a total of 18,248 seeds on the target faults. Next, one image patch of the original
post-stack amplitude is retrieved in a size of 31 inlines by 31 samples centered about each of the labelled seeds. Finally, these images are resampled to be 32 by 32 to facilitate the convolution and pooling operations used in the CNN convolutional layers.

Figure 1 The diagram for illustrating the proposed workflow of CNN-based seismic fault detection with three major components: training image preparation, CNN classifier training, and volumetric processing.

B. CNN classifier training. Figure 2 illustrates the architecture of the simplest 1-layer CNN network used for fault classification in this study. In particularly, it consist of one convolutional layer followed by one fully-connected layers. The input seismic images are 32 by 32. The convolution masks have a size of 9 by 9. The convolutional layer generates 16 features. The 2x2 maximum pooling is used to reduce the dimensions of output features after convolution and hence to control overfitting. The dropout technique (Hinton et al., 2012) is also used to avoid overfitting by preventing complex co-adaptations on training data. The fully-connected layer has 1024 neurons, and the softmax cross entropy is computed for measuring the probability error between the classification and the true labels. The prepared 318,240 images are used for training the CNN network in 300 epochs. Cross validation is applied for verifying the accuracy of the trained CNN classifier. The activation function at all neurons are initialized as noises in normal distribution with the standard deviation of 0.1, and are updated while the training continues.

Figure 2 The diagram for illustrating the architecture of the 1-layer CNN classifier used for fault detection in this study.

C. Volumetric processing. The trained CNN classifier is applied to the entire seismic survey for generating a fault volume. At each seismic sample, an image patch of 31 crosslines by 31 samples is first retrieved from the original amplitude and then resampled into 32 by 32. Then its label is predicted by the trained CNN classifier and assigned to the central sample.

Results

For demonstrating the accuracy of the proposed CNN approach, we first compare the results with the traditional multi-attribute based classification methods. Figure 3 displays the comparison of the crossline section #2800, among which we notice that the CNN result is clean and closest to the manual interpretation. Next, for addressing the concern of overfitting, Figure 4 displays the clipping of the generated fault volume to four randomly-selected vertical sections that were not used in the training process. It is clear that, the CNN classification successfully detects the faults as thin lineaments,
indicating that the trained CNN classifier is capable of learning the target seismic features from the original post-stack seismic amplitude and detecting the identical ones accurately.

Figure 3 A comparison of labelling the faults using the traditional multi-attribute based SVM (b) and MLP (c) and the proposed CNN (d) in the crossline sections #2800. The manual fault interpretation is shown in (a). Note that the CNN detection is the closest to the manual interpretation.

![Figure 3]

Figure 4 The clipping of the fault volume (in black) by the 1-layer CNN network (Figure 2) to four randomly-selected vertical sections, including inline #1791, inline #2011, crossline #2600, and crossline #3000 from left to right, overlaying the original seismic amplitude (in blue-white-red). Note the good match between the CNN detection and original images.

Finally, for better understanding the performance of the CNN technique, Figure 5 displays the 16 features automatically generated from a given seismic images. We notice that: first, the CNN features are of little physical meaning but only slightly different from the original seismic image, implying that the convolutional masks are simple in math compared to the existing attribute algorithms (e.g., coherence, curvature, and GLCM); second, although the faults remain implicit in each of the CNN features, the following full-connected layer successfully integrates these implicit features and maps them with the fault labels in a more accurate way, indicating the better grouping of the faults and non-faults in the 16-dimensional domain constructed by the CNN features.

Figure 5 The 16 features automatically generated by the 1-layer CNN network (Figure 2) for a given seismic image (left). Note that all the features appear similar to the original amplitude.

Conclusions

This study has adapted the state-of-the-art convolutional neural network (CNN) technique to work for seismic fault detection. Compared to the traditional multi-attribute based techniques, the CNN network
is capable of optimally connecting the seismic images with the target faults using the original post-stack amplitude, instead of manually selected seismic attributes, so that the entire process saves interpreters lots of efforts in selecting and generating seismic attributes. Moreover, the CNN classifier utilizes the local seismic reflection patterns, instead of stand-alone attribute values, so that the seismic noises and processing artifacts of distinct patterns can be effectively identified and excluded. The good match between the generated fault volume and the original seismic images not only verifies the capability of the CNN tool in assisting seismic fault interpretation, but also indicates greater potential for implementing more advanced machine learning techniques (e.g., FCN) into analysing, understanding, and interpreting seismic signals.

References


