Seismic Fault Detection using Neural Networks

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Summary

Fault detection and understanding of fault evolution are crucial in exploring and developing hydrocarbon resources and for assessing sites for carbon storage and sequestration. Success in these fields requires accurate identification of faults and fractures and investigation into how they may affect fluid migration and how they influence porosity and permeability. On seismic reflection sections, manual fault-picking, even for highly skilled experts, is very time-consuming, Consequently, many semi-automated methods have been proposed, with Peters et al. [2019] and Li et al. [2018] recommending the use of deep learning-based approaches. The aim of this abstract, with the help of the Wrona et al. [2021] GitHub workflow, is to perform automated fault detection by using a deep neural network on 2D seismic reflection sections. Traditionally, such approaches (e.g., Zhang et al., 2014; Araya-Polo et al., 2017; Wu and Fomel, 2018; Wu et al., 2019; Mosser et al., 2020; Feng et al., 2021) have used parts of a single seismic line to train and validate their fault picks. In this work, we use several different 2D seismic lines for training and testing. This allows for our approach to predict faults along unseen seismic lines, which will be more applicable in the industry for frontier basins with only sparse 2D seismic coverage.

Theory / Methodology / Workflow

Deep learning has changed how big data are analyzed in many scientific fields worldwide (Wrona et al. 2019). Multichannel seismic reflection surveying provides one of the best methods for estimating the subsurface properties of the Earth. However, analysis of the resulting large datasets requires significant expertise and time.

In recent years, advances in machine learning using multi-layered neural networks (i.e., deep learning) have been applied to numerous problems in seismic interpretation, including fault detection (e.g., Zhang et al., 2014; Araya-Polo et al., 2017; Wu and Fomel, 2018). The workflow of the proposed method for seismic fault detection has two main parts: *training* and *prediction*. The training part itself involves *preprocessing* and *model training*.

When it comes to deep learning, *preprocessing* is an essential step, which was divided into five steps:

I. Reprocessed 2D seismic reflection amplitude sections from block WA-484-P in the North Carnarvon Basin in North-Western Australia (downloaded from Geoscience Australia) with dimensions of $a \times b$ are converted into 2D RGB images with the same size, i.e., the image size is $a \times b$, and each pixel value is an integer in the range of~0–255.

II. The seismic sections are manually divided into four coarsely defined stratigraphic units based on seismic attributes such as coherency, variance, and curvature. This helps compartmentalize the coeval fault trends.

III. To use a deep learning approach for fault detection, sufficient training data must be fed into the neural network; here, we used supervised fault labeling on 12 of 13 seismic sections. The labels have a binary value of 1 for faults and 0 for non-faults.

IV. Data in the range [0-255] are normalized to [0-1], and a moving window is applied with a window size of 64×64 and centers moving with a step size of 10 across the entire section.

V. As the volume of data is large, hardware restrictions arise, so to solve this problem, the seabed and noisy deeper parts of the seismic section are omitted from the analysis.

For *training the model*, it is essential to define its architecture. To yield more precise segmentation, the chosen model is the state of the art U-Net (Mobilenet variation) Convolutional Neural Network with a sigmoid activation function at the output layer to clarify two classes (fault and non-fault), an ADAM optimizer, and a Dice loss function with a patch size of 64×64. For training and testing the convolutional neural net, the data were gathered from 13 different seismic sections (12 sections for training and 1 section for development). For testing, we have not involved seismic line dc98-213-a in training and reserved it as unseen data. The training was run for 70 epochs to reach 10^{-1} as, the lowest loss value.

Results, Observations, Conclusions

Prediction: As stated, only segments 2 and 3 of the 12 sections are used for training the model. The trained model is able to predict the faults in segment 4 of these sections, which represents unseen data, too. Additionally, the methodology was also able to detect faults with reasonable visual accuracy in parts of the model that had not been seen before and that were only considered for prediction. (Figure1-b).

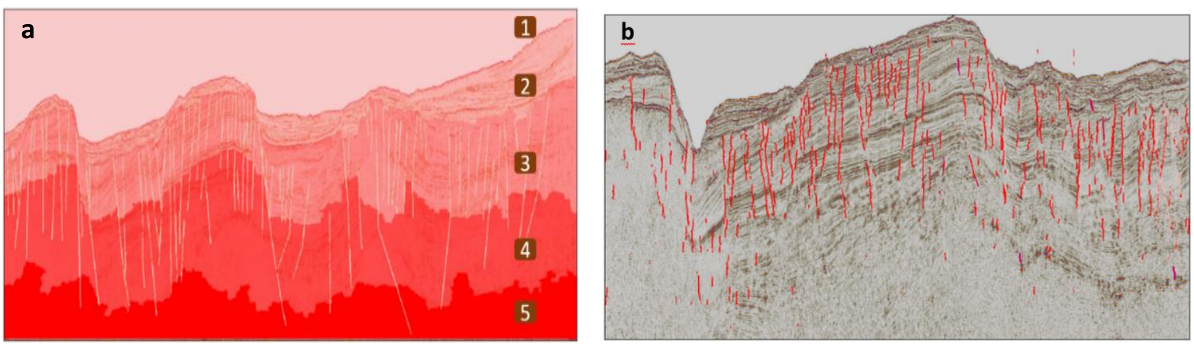

Figure 1: (a) Seismic line dc98-214, in which the faults are labeled manually. Segments 1 to 5 are roughly divided based on the approximate times of deposition. Segment 1 (sea-bed) and segment 5 (deep noisy section) are not used for training and validation. (b) The predicted result is Seismic line dc98-213-a, which was not involved in the training, representing unseen data.

Further steps

For *the postprocessing step:* we are now looking at ways to automatically extract fault population statistics from the predicted fault images.

Reference

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