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Seismic Fault Detection within the Jeanne d'Arc Basin Using a Modified U-Net

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Summary

Detection and extraction of faults in seismic data are important challenges in interpreting such data, particularly for identifying hydrocarbon traps, evaluating reservoir potential, reservoir modelling, identifying subsurface structures for energy resource management, identifying high-risk earthquake zones, and designing carbon storage and geothermal energy projects. Fault picking on seismic sections is time-consuming and requires skilled experts, often subject to subjective interpretation errors. These limitations have prompted researchers to develop semi-automatic and automated methods for fault detection. This study builds on previous workflows to automate fault detection using a deep neural network. We applied our approach to seismic reflection sections from the Jeanne d'Arc Basin offshore Newfoundland. Our approach enhances fault identification accuracy, reduces manual interpretation efforts, and improves efficiency.

Theory / Method / Workflow

Multichannel seismic reflection surveying is a powerful technique for assessing Earth's subsurface, but processing and interpretation require significant expertise and time. These limitations have prompted researchers to develop semi-automatic and automated methods for fault detection, like Peters et al. [2019] and Li et al. [2018], recommending deep learning-based approaches. These approaches can perform advanced feature extraction and pattern recognition with high precision. The U-Net algorithm, originally developed for biomedical imaging, has shown remarkable success in seismic applications due to its flexibility, minimal data requirements, and compatibility with standard hardware, making it ideal for feature extraction and segmentation. Our approach follows a two-phase workflow: development and evaluation. The development phase includes model selection, data preprocessing, and training, while the evaluation phase involves validation, fault prediction, and post-processing for refinement and statistical analysis. We adopted and customized the U-Net-based workflow of Wrona et al. (2021) for pixel-by-pixel fault classification to best capture the structural complexity within the basin. While their model is designed for 3D North Sea data, we apply it to 2D seismic sections extracted from within a 3D cube from the Jeanne d'Arc Basin, offshore Newfoundland, and Canada. In our adaptions, we test multiple backbone architectures, including VGG16, VGG19, ResNet18, ResNet34, EfficientNetB0, and MobileNet. We choose MobileNet-V2 for its lower parameter count, faster training, and high accuracy. In our U-Net model, MobileNet-V2 acts as the encoder, leveraging efficient feature extraction, while the decoder employs skip connections to enhance spatial retention for fault detection. We optimize our model through experimentation with data augmentation, dropout, loss functions, and layer configurations, with a decoder size of (256, 128, 64, 32, and 16) and Dice loss. This configuration, comprising 6.6 million parameters, is trained for 100 epochs, and gives a final loss of 0.05 using the ADAM optimizer.

Results, Observations, Conclusions

For an unbiased evaluation of our model's performance, we designate one seismic line solely for validation and another separate line specifically for prediction.
We present the results of applying our model to unseen data, as shown in Figure 1, demonstrating its ability to accurately detect faults and validating its effectiveness.
-Because of the highly imbalanced nature of our dataset, where non-fault pixels significantly outnumber fault pixels, we use the Tversky index **(Tversky, 1977)** as our primary evaluation metric. This index incorporates two parameters, α and β, which control the relative weighting of false positives and false negatives, making it particularly suitable for fault detection. In this study, we set α = 0.7 and β = 0.3. A Tversky index score of 77% indicates strong agreement between the model's predictions and the ground truth.

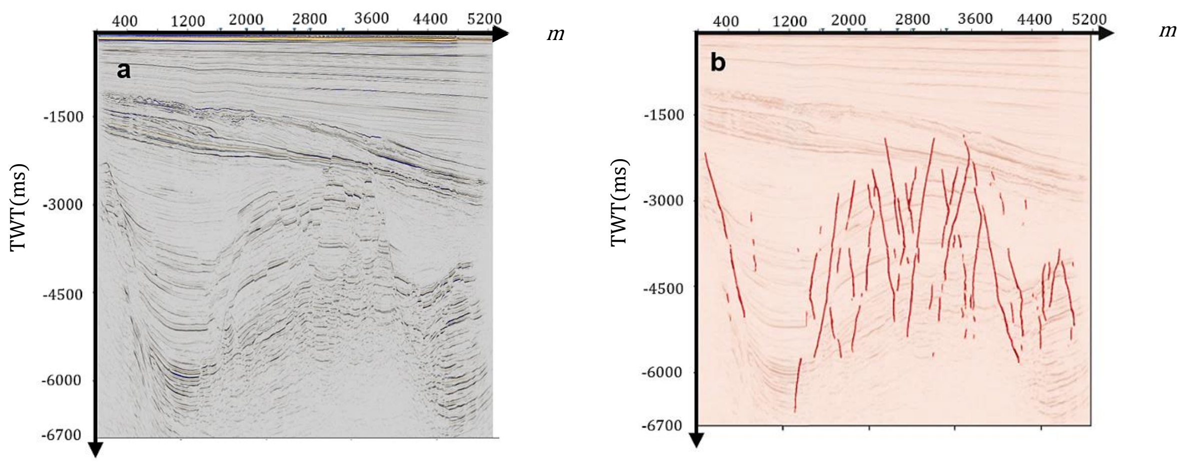

Figure1: This seismic line, was reserved exclusively for prediction and was not involved in the training and validation phases. (b) Predicted faults (red lines) along the seismic line.

Further steps

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

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