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Evaluating and improving efficiency 3D CNN-based Fault detection in brazilian pre-salt

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Abstract

This paper presents an enhanced 3D U-Net convolutional neural network (CNN) architecture tailored for fault segmentation tasks. We generated synthetic training datasets using realistic structural features and noise characteristics derived from real seismic data, augmented systematically through rotations and flips. The network employs balanced cross-entropy-dice loss to effectively manage class imbalance and enhance segmentation accuracy. Application of this methodology to seismic data from the Brazilian pre-salt demonstrates improved fault detection capabilities, significantly reducing noise and improving continuity in comparison to previous models. Results indicate the promise of CNN-based approaches for complex geological settings, although further optimization is recommended.

Introduction

Accurate fault detection in seismic interpretation is crucial for reservoir characterization and hydrocarbon exploration. Traditional attribute-based methods often face challenges such as sensitivity to noise and limitations in detecting complex structures (Hale, 2013). Recent advancements in deep learning, particularly convolutional neural networks (CNNs), offer significant improvements in fault detection accuracy and efficiency (Wu et al., 2019; Li et al., 2024). CNN-based approaches, especially the U-Net architecture, enable end-to-end seismic fault segmentation, leveraging automated feature extraction and classification capabilities (Wu et al., 2019; Li et al., 2024). However, CNN methods require extensive labeled datasets and optimal training strategies to achieve generalization and robust performance.

Training data and Network hyperparameters

In this study, we implemented a simplified 3D U-Net architecture specifically tailored for fault segmentation tasks. The network comprises multiple layers of 3D convolutional, pooling, and upsampling operations, designed to capture hierarchical fault features efficiently (Wu et al., 2019).

In the contraction path (left side), each step consists of two 3 × 3 × 3 convolutional layers, followed by a ReLU activation and a 2 × 2 × 2 maxpooling operation with stride 2 for downsampling. Each step in the expansion path (right side) contains a 2 × 2 × 2 transposed convolution operation, a concatenation with the patterns from the contraction path, and two 3 × 3 × 3 convolutional layers followed by a ReLU activation. Because we believe this is a more complex problem, we add an additional layer, making the network deeper. We tested using batch normalization and adding dropout layers, but we did not obtain any improvement in the result. The final output layer is a 1 × 1 × 1 convolutional layer with a sigmoid activation (Figure 1).

Training data were generated synthetically, incorporating realistic structural and stratigraphic features and noise patterns derived from field seismic data to enhance the model's generalizability. Additionally, the synthetic seismic data were produced using the Point Spread Function (PSF) to simulate realistic seismic response characteristics, improving the fidelity of the synthetic dataset to real-world seismic acquisitions (Jing et al. (2023)). Data augmentation, including rotations and flips, was systematically applied to enrich training variability and improve robustness.

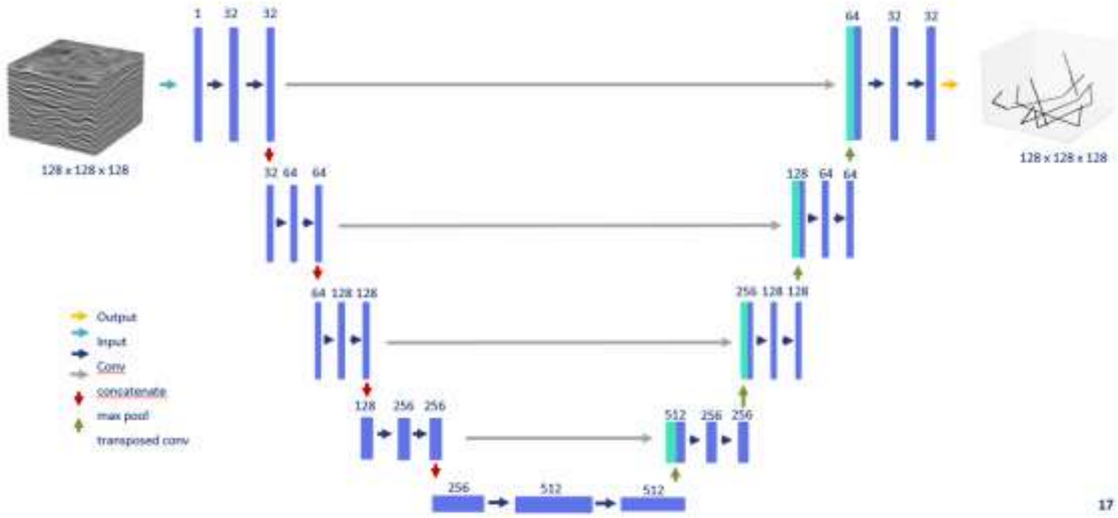

Figure 1: Unet's architecture proposed by Wu et al., 2019.

Using this methodology, we created 200 pairs of 3D synthetic data measuring 128x128x128. We could have created a larger amount of data, but for comparison purposes with works previously proposed by other authors, we restricted ourselves to this amount. However, data augmentation techniques were applied, such as rotation by 90º, 180º and 270º. To optimize training, we adopted a balanced cross-entropy-dice loss function, effectively addressing class imbalance and improving segmentation accuracy (Li et al., 2024).

Analyzing the training curves (Figure 2), it is possible to notice that after epoch 25, the network suffers from overfitting. To avoid this, epoch 20 was used for prediction, which, despite not achieving its most optimal result, was able to identify the main trends with good continuity and less noise.

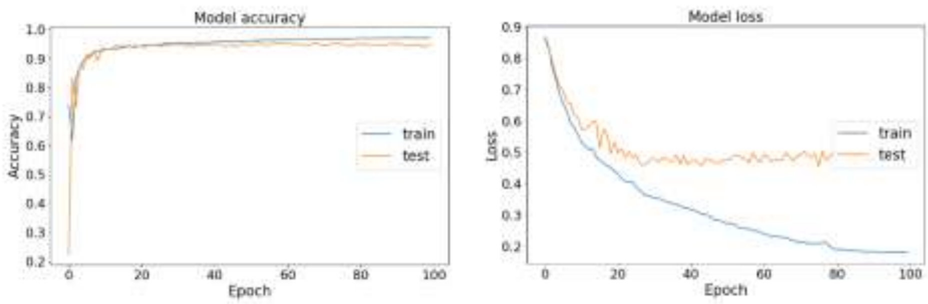

Figure 2: Loss function and accuracy curves for training and validation

Results

The Búzios field is one of the main producers in the Brazilian pre-salt layer (Figure 3). The pre-salt carbonate reservoirs were deposited under a thick layer of salt at great depths (approximately 5,000 meters), representing a challenge for seismic imaging and illumination. The data application of this work has an ocean-bottom nodes (OBN) seismic acquisition with broadband spectrum, capturing geological information at lower and higher frequencies compared to older data, where the bandwidth is narrower (Figure 3)

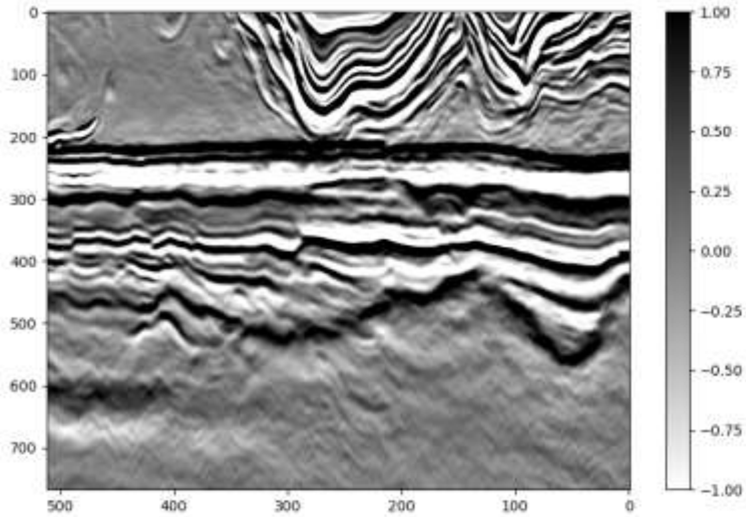

Figure 3: Crossline section of field data standardized used to predict the pretrained model.

In their comprehensive evaluation, Li et al. (2024) demonstrated that adopting a novel loss function, such as the balanced cross-entropy-dice loss, significantly enhanced the segmentation accuracy and generalization performance of CNN models in seismic fault detection. Their experiments indicated that traditional pixel-based loss functions could not adequately handle complex geological structures and subtle fault features.

Seeking to improve the results obtained by Nilo et al. (2024), changes were made to the model architecture, the construction of the synthetic data and the loss function used. For computational reasons, the best model with hyperparameter optimization is not yet available, but initial results were optimistic compared to previous ones (Figure 4).

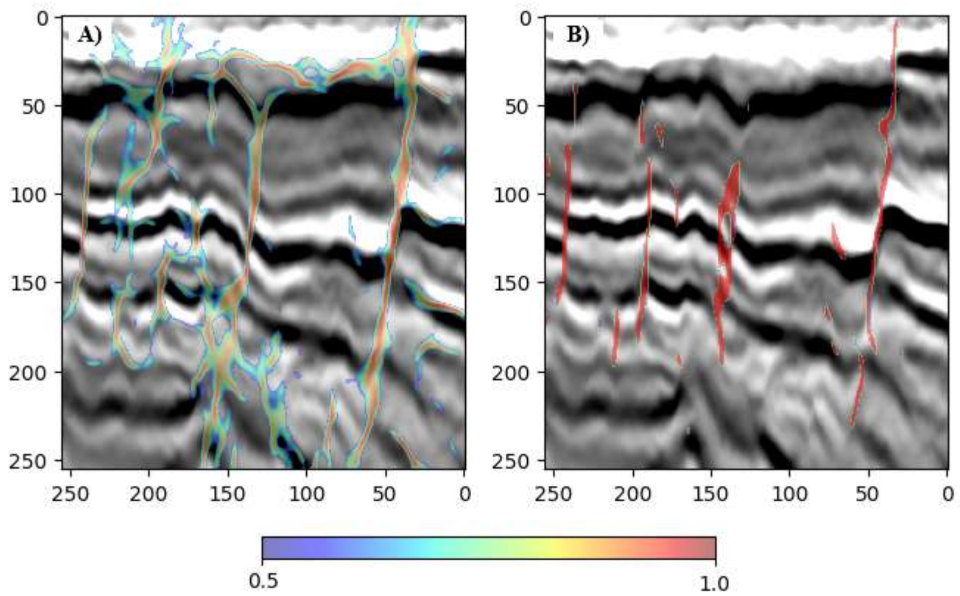

Figure 4: In A) prediction results obtained by Nilo et al. (2024); In B) After loss change and trained with new synthetic data.

Conclusions

This study demonstrated the effectiveness of a modified 3D U-Net CNN architecture in seismic fault segmentation, achieving noticeable improvement over previous approaches. Generating synthetic seismic data that accurately reflect realistic geological conditions and employing a balanced cross-entropy-dice loss function significantly enhanced fault detection accuracy and generalization capability. The network was able to identify main structural trends with good continuity and reduced noise. Despite the promising results, further optimization, particularly involving hyperparameter tuning, is necessary to maximize the method's potential fully.

Acknowledgments

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References

Hale, D. (2013). Methods to compute fault images, extract fault surfaces, and estimate fault throws from 3D seismic images. Geophysics, 78(2), O33-O43.

Jing, J., Yan, Z., Zhang, Z., Gu, H. and Han, B. [2023] Fault detection using a convolutional neural network trained with point-spread function-convolution-based samples. Geophysics, 88(1), IM1–IM14.

Li, Y., Wu, X., Zhu, Z., Ding, J., & Wang, Q. (2024). FaultSeg3D plus: A comprehensive study on evaluating and improving CNN-based seismic fault segmentation. Geophysics, 89(5), N77-N91.

Nilo, M., Fernandes, F. J. D., Neto, E. R. O., Teixeira, L., & Lupinacci, W. M. (October 2024). *Seismic fault interpretation using deep learning in the Búzios field*. Paper presented at the 10th Brazilian Symposium on Geophysics, Salvador, BA, Brazil. Brazilian Geophysical Society.

Wu, X., Liang, L., Shi, Y., & Fomel, S. (2019). FaultSeg3D: Using synthetic data sets to train an end-to-end convolutional neural network for 3D seismic fault segmentation. Geophysics, 84(3), IM35-IM45.