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Interactive Deep Learning for Rift Faults Interpretation on 3D Seismic: A Case Study in Iara Cluster, Santos Basin

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Summary

This is a case study involving data from the Santos Basin, specifically the Iara region. Based on the seismic data from this area, a workflow was developed and applied using Deep Learning to create Pre-Salt Faults. In an exploratory context, the generated faults present good detail and geometry showing the relevance of data-centered Artificial Intelligence Models.

Introduction

The Santos Basin is in the southeast region of the Brazilian continental margin, between parallels 23º and 28º South, occupying approximately 350,000 km^2 up to the bathymetric level of 3,000 m. It covers the coasts of the states of Rio de Janeiro, São Paulo, Paraná and Santa Catarina, bordering the Campos Basin to the north by the Cabo Frio High and the Pelotas Basin to the south by the Florianópolis Platform (Moreira et al., 2007).

The characterization of a petroleum system is essential to understand how hydrocarbon generation, migration, accumulation and preservation occur. A detailed analysis of the source rocks, reservoirs, seals and traps allows the identification of promising areas and reduces exploration risks. Among these elements, fault systems play a fundamental role, as they can function as pathways or barriers for migration, influencing the accumulation of hydrocarbons. Faults can create structural traps by placing reservoir rocks in contact with impermeable seals.

Seismic interpretation of the Santos area points to a model with the occurrence of structural highs in the basement controlling the accumulation of hydrocarbons in carbonate and siliciclastic reservoirs (Chang et al., 2008). Generation occurs in the structural lows of the same section and migration occurs by carrier-bed to the apex of the structures, which present excellent closure geometry (Chang et al., 2008).

In the Santos Basin, Iara Cluster is a massive pre-salt structure with more than 300 km² of extension in the northeast portion of the Santos Basin which encompasses three of the biggest accumulations of the basin: Sururu, Berbigão and Atapu. The first exploratory efforts in this area started in June 2000, with the concession of the BM-S-11A block from the 2nd Bidding Round under the Concession Regime (Vital et al., 2022). In January 2025, seven of the thirty most productive oil fields in Pre-Salt are in the Iara Cluster area. Together they are responsible for 11.03% of the total BOE/day (National Agency for Petroleum, Natural Gas and Biofuels, 2025).

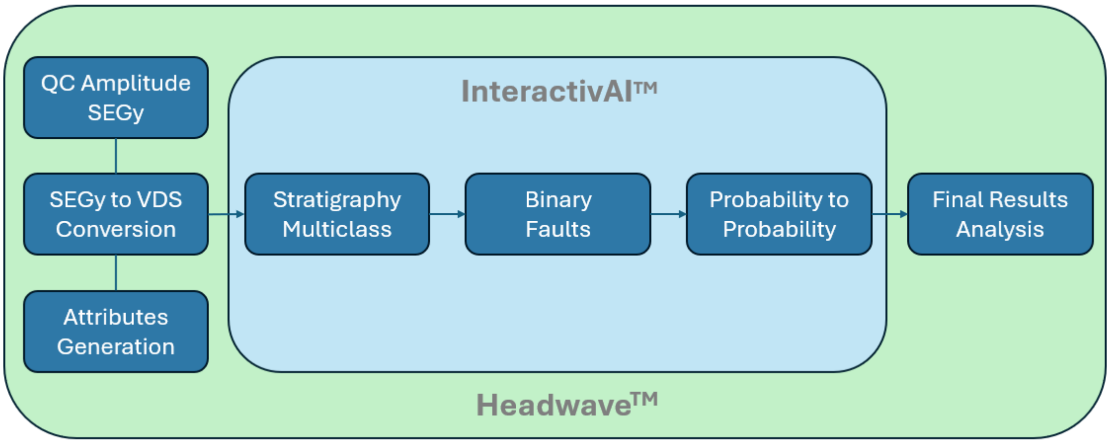
Thus, the objective of this work is to characterize the fault system in the Iara area through an innovative approach using interactive Deep Learning.

Method

Platforms

For this case study two applications were used. One for the initial SEGY Quality Control (QC) in a 3D view, conversion from SEGY to VDS, seismic attributes calculation and final products analysis. The goal of the second software was to serve as Deep Learning User Interface to extract insights of seismic data (Diagram 1).

Diagram 1 - Fault System Assessment Workflow using a UI Deep Learning.



Data

In this work, only seismic data was investigated as subsurface relevant source of information. The data came from PROMAR public data source from ANP. Among many seismic surveys one from the Iara Cluster was chosen.

The original SEGy file has 22.1 GB. A brief QC was performed to check the data before effecting the VDS conversion. The VDS converted has 5.50 GB and this process was done through a Wavelet Transform with an overall compression tolerance of 1.

Two attributes were calculated from the amplitude VDS. First an Instantaneous Frequency to check how the frequency signal is distributed along the data, especially below the salt layer. The initial cutoff frequency parameter was 2 Hz. And then the RMS to possibly have an image with better discontinuities illuminated. The window length parameter was 9 ms.

Stratigraphic Mask

The main goal of this work is to have the fault system of Iara Pre-Salt interpreted. This task was done supported by a Deep learning tool that works in convergence way. By these words it means that the workflow should start from a large to small scale. In seismic context this translates into the mapping of Stratigraphy Mega Sequences. This mapping generates probability cubes from the mapped intervals that can serve as mask to the next steps, mapping Pre-Salt faults.

The Stratigraphy Mega-Sequencies mapped were five described into: water column, post salt, salt, pre-salt and basement. The Deep Learning architecture was E-Net and running in parallel on two seismic volumes, Raw Amplitude and RMS. The loss function chosen was Categorical Cross Entropy. 0.2% lines were added as labels (12 of 5922 lines) and 15 epochs running.

Faults Part 1

The first part of the faults labeling uses the initial multiclass probability cube to mask out all the stratigraphy intervals besides the pre-salt. In this way, the deep learning network learns fast as it is looking just at this specific interval from the entire seismic volume.

The faults were labeled using a E-Net binary network searching in just the raw amplitude volume. The loss function chosen was Weighted Root Mean Square Error. 0.15% lines were added as labels (9 of 5922 lines) and 6 epochs running.

Faults Part 2

The second part of the fault interpretation is called Probability to Probability (P2P). This step aims to improve the results of the previous step. The P2P will improve continuity and sharpness of the Fault Probability cube. The workflow consists of labeling the previous fault probability cube and generate inferences based on this.

Faults were labeled using an E-Net binary network searching in the fault probability cube volume. The loss function chosen was Weighted Root Mean Square Error. 0.03% lines were added as labels and 2 epochs running.

Discussions and Results

With one week work, 5 classes were interpreted dividing the data between what was called Water, Post Salt, Salt, Pre Salt and Basement (Figure 1). In addition to generating the interface horizons of each mapped interval, probability cubes were created and used as a mask for labeling Pre-Salt faults.

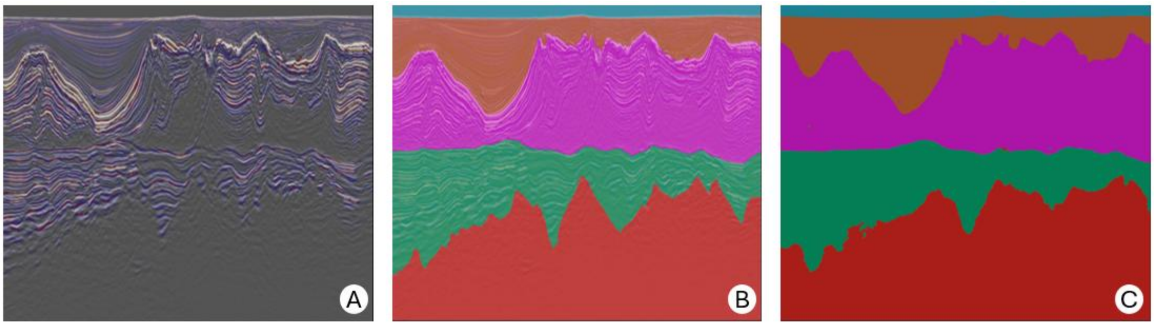


Figure 1 - Seismic Amplitude and RMS blended (A); Classes Label and Seismic blended (B); Probability Cube (C).

The creation of a fault model based uniquely on the seismic data and the labels created made it possible to generate a concise view of faults through probability cubes, which in turn generated coherent and continuous sticks in accordance with the seismic data.

The applied workflow removed the need to manually connect fault planes. Interpretation or labeling did not need to be done on a regular mesh. The results are very detailed (Figure 2) compared to manual interpretation.

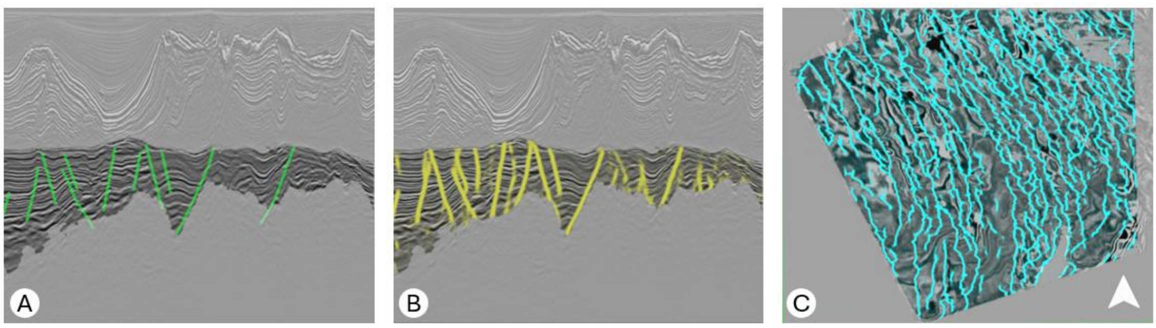


Figure 2 - Fault Labels on Pre-Salt Layer (A); Fault Inferences on Pre-Salt Layer (B); Fault Probability Cube on map view (C).

Conclusions

The use of Deep Learning to interpret Rift-type faults in an exploratory block in the Santos Basin led to some insights:

- The use of Deep Learning in the presented context provided excellent results on an exploratory scale when it comes to generating horizons.
- The work shows that generating faults in this way generates geologically coherent results with rich details that a manual interpretation at production time would not be able to accomplish.
- With less than a month of work it was possible to go through the seismic data from the exploratory scale to the reservoir, implementing an interpretation of the macro with the mega sequences to the micro in detailing the labeling of faults.
- On the same Deep Learning platform, Geobodies, Horizons and Fault Planes were generated, which together contribute to the interpretation and understanding of the geological context of the area.

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