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Convolutional Neural Network for Horizon Interpolation in Geophysical AI Software

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Introduction

Identifying horizons is a fundamental step in seismic data analysis, particularly in gas and petroleum exploration, as these structures can reveal information about where reservoirs are likely to be located and help define their geometry. Traditionally, this process is performed manually by geophysicists, often leading to time-consuming and labor-intensive efforts that are prone to human error and subjectivity. To overcome these limitations, Artificial Intelligence (AI), particularly machine learning techniques, offers a promising avenue to assist geophysicists in the accurate and efficient identification and interpolation of seismic horizons.

This study presents a methodology based on Convolutional Neural Networks (CNNs) to semi-automate the detection and interpolation of seismic horizons. The method is a core component of a broader AI software system for geophysical interpretation, designed to reduce the effort required in horizon detection tasks. The approach processes 2D slices of 3D seismic data using a pre-interpreted horizon model with sparse points to delineate subsurface structures more efficiently.

Method and/or Theory

The horizon detection methodology employs a neural network-based approach that processes seismic data through several key steps. The framework starts by loading and normalizing both seismic data and a reference mask, then processes the information in 3D volumes using a trained model to predict horizon locations. The process includes window-based analysis (with configurable window sizes), normalization of seismic amplitudes, and the application of a deep learning model that outputs probability maps for horizon presence.

The model generates a prediction volume where each voxel stores the probability of belonging to a horizon. This volume is reshaped to match the original seismic dimensions and is converted into a point cloud. Post-processing techniques are then applied, such as DBSCAN (Density-Based Spatial Clustering of Applications with Noise), to remove noise and cluster valid horizon points. Finally, a thinning algorithm is applied to refine the horizons by selecting the most significant points based on amplitude values.

Results and Conclusions

The proposed methodology produces three main outputs: a refined 3D mask of the detected horizon, amplitude values associated with each point, and a data frame with horizon coordinates. These results include precise x, y, and z coordinates and amplitude values, which are then transformed into the project's coordinate system through rotation and scaling. The final output is stored in a NetCDF file, allowing 2D and 3D visualization of the results. The quality of detection is influenced by parameters such as the probability threshold, clustering settings, and model training quality. This methodology has shown successful results in the F3-Block and Mexilhão Field, even under complex geological conditions, using models like UNET, UNET++, and Attention-based architectures. Future work aims to integrate this methodology into a fully automated framework using Relative Geologic Time (RGT) to identify horizons throughout 3D seismic volumes.