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Comparative Analysis of Model-Based Acoustic Seismic Inversion Methods

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Abstract Summary

This study presents a comparative analysis of two model-based seismic inversion methods: Maximum Likelihood (ML) and Sparse Spike (SS). A synthetic seismic cube was created using a Point-Spread Function (PSF) and the Butterworth wavelet to evaluate the performance of these techniques under controlled conditions. Metrics such as Mean Absolute Percentage Error (MAPE) and Pearson correlation coefficient were applied to assess the results. The findings revealed that the ML method consistently achieved better accuracy, showing lower errors and higher correlation with the reference model, while SS exhibited limitations in handling high-frequency variations and produced noisier results. These results emphasize the suitability of ML for acoustic impedance inversion, especially in scenarios characterized by structural complexity and low-frequency seismic data. Future research should focus on optimizing the SS algorithm to broaden its applicability in geophysical contexts.

Introduction

Seismic inversion is essential for estimating subsurface elastic properties by integrating seismic data with geological and petrophysical information (Adler et al., 2021; Lin et al., 2022). Among the available approaches, model-based acoustic inversion is widely adopted in post-stack workflows to retrieve acoustic impedance from seismic traces, using well logs as constraints (Kushwaha et al., 2023). In this context, we compare the Maximum Likelihood and Sparse Spike methods using synthetic datasets that replicate diverse geological settings. The analysis considers both accuracy and robustness under frequency-limited conditions, aiming to identify the more effective technique for complex interpretation scenarios (Ali et al., 2024).

Method and/or Theory

This study used a synthetic seismic cube (256^3) generated via 2D convolution between reflectivity and a Butterworth-based point-spread function (PSF). To simulate realistic conditions for comparing Maximum Likelihood (ML) and Sparse Spike (SS) methods, a low-pass filter was applied to create a 6 Hz low-frequency model for inversion input. Additionally, a 30 Hz impedance model served as the reference for performance evaluation. The Butterworth wavelet was generated using high- and low-cut filters, while the Ricker wavelet was defined by its peak frequency of 30 Hz.

The inversion used linear modeling operators from PyLops to simulate the seismic-wavelet convolution. L2-norm regularization was applied to stabilize the least-squares solution and reduce noise sensitivity (Eq. 1).

(A) $S(m) = |\mathbf{Gm} - \mathrm{d}|_2 - \lambda|(\mathbf{m})|_2$ (B) $S(m) = |\mathbf{Gm} - \mathrm{d}|_1 - \lambda|(\mathbf{m})|_1$

Equation 1 – (A) Objective function of the sparse spike inversion. (B) Objective function of the sparse spike inversion.

The SS method applied L1-norm regularization via the IRLS algorithm, which iteratively adjusted model weights for stable convergence under noisy conditions (Eq. 2). Adjustments were made to handle zero-residual elements and ensure computational stability.

Equation 2 *– Objective function of the sparse spike inversion.*

Inversion results were evaluated through both qualitative and quantitative analyses. Accuracy was measured by Mean Absolute Percentage Error (MAPE), and linear correlation by the Pearson coefficient, comparing inverted models to the reference. Visual assessments included seismic sections and histograms of impedance values. Implemented in Python, this approach enabled efficient handling of large datasets and a systematic comparison between ML and SS methods.

Results

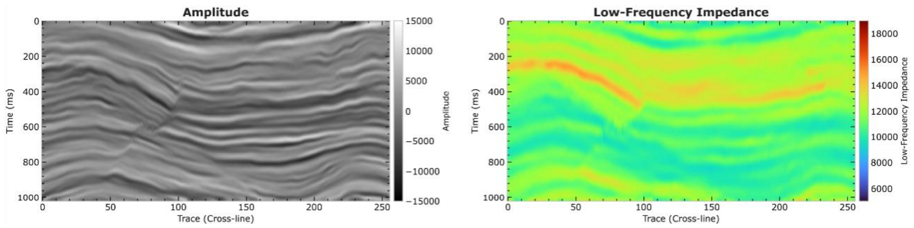

Figure 1. Original synthetic session, showing the amplitude and the low-frequency impedance.

In Figure 1, amplitude data have intermediate frequencies, while low-frequency impedance shows limited spectrum. This contrast highlights seismic inversion's role in reconstructing impedance and improving fault and discontinuity detection.

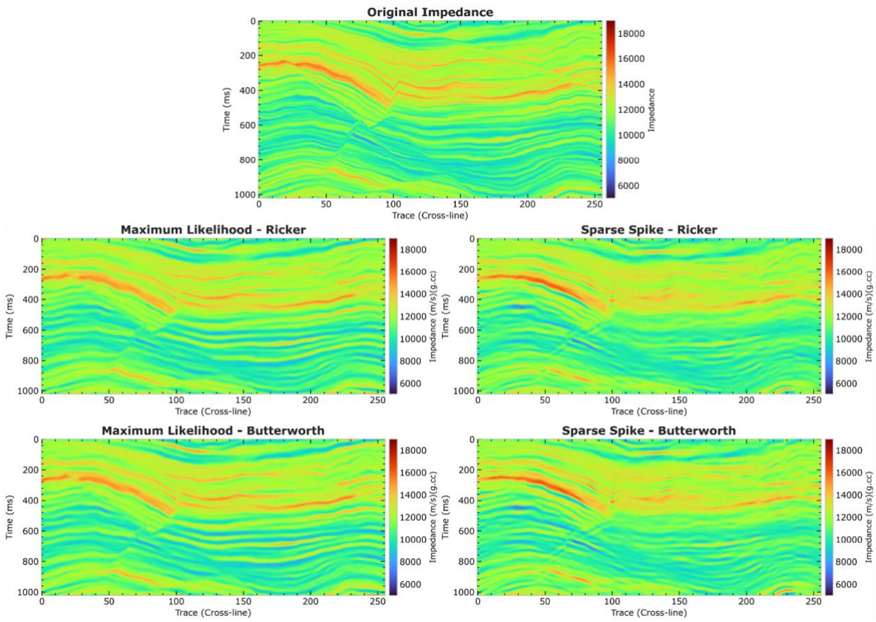

Figure 2. Seismic section at trace cross-line 128, showing the Maximum Likelihood and Sparse-Spike inversions with both wavelets.

In othe sections, ML showed less noise and better fit, especially in high-impedance zones. SS, favoring sparsity, introduced more artifacts in discontinuous areas. Both methods, however, detected key faults between traces 50 and 100, confirming their effectiveness in complex synthetic scenarios.

Quantitative Analysis

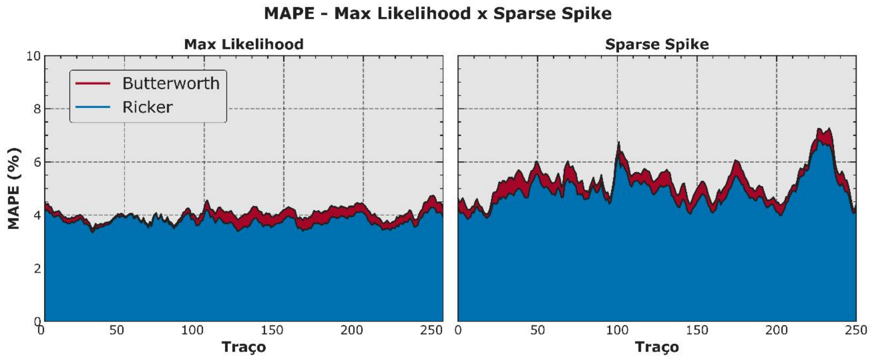

Figure 3. Comparative MAPE plot of the Maximum Likelihood and Sparse-Spike inversions

MAPE results (Fig. 3) showed ML inversion performed better, with 3.50% error using Ricker and 3.75% with Butterworth wavelets. SS inversion had higher errors, 5.63% (Ricker) and 6.04% (Butterworth). Despite the data being generated with Butterworth, Ricker outperformed it, indicating frequency content and low-frequency model adaptation challenges. SS's lower performance likely stems from convergence issues typical in impedance inversion.

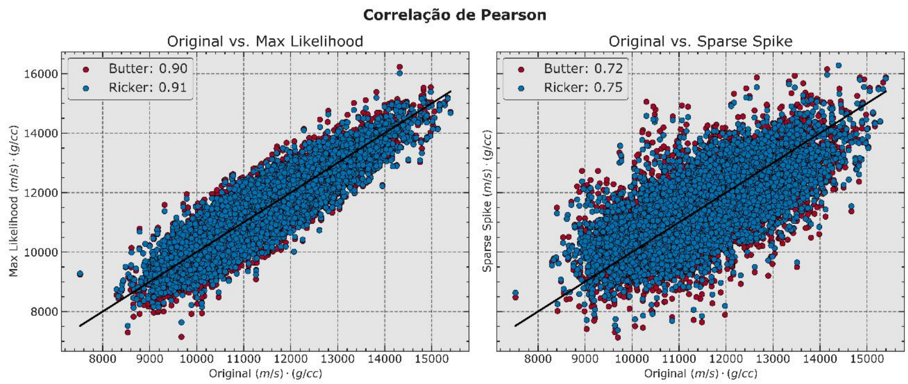

Figure 4. Pearson coefficient calculated based on a random sample corresponding to 0.01% of the data. The sample has 16 thousand elements, selected from 16 million elements.

In Fig. 4, the dispersion of the original data and the inversions is observed, which was performed using a random sample corresponding to 0.01% of the result. The lower dispersion in the ML method is consistent with its higher average correlation. On the other hand, SS showed greater dispersion, highlighting the method's difficulty in recovering high frequencies.

Conclusions

The results show that, for the synthetic dataset used, the Maximum Likelihood (ML) method consistently outperformed Sparse-Spike (SS) in both qualitative and quantitative assessments. ML produced seismic sections with less noise and better reconstruction near fault zones (Bosch et al., 2010), while SS showed more dispersion and peak-focused artifacts that hindered accurate impedance recovery (Zhang & Castagna, 2011). Quantitatively, ML achieved lower MAPE values (3.50% with Ricker, 3.75% with Butterworth) compared to SS (5.63% and 6.04%), and higher Pearson correlations (0.91 and 0.90 vs. 0.75 and 0.72). These findings highlight ML's robustness and reliability for acoustic impedance inversion in controlled conditions, and in this specific case. Still, given the use of synthetic data, further studies are needed to enhance SS performance and validate these results in real-world applications.

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