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Sparse Matching for 4D Response Estimation in the Marlim Sul Field

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Abstract

This work presents a methodology for estimating the 4D reservoir response in the Marlim Sul field using rigid sparse matching techniques. The approach enhances the accuracy and signal-to-noise ratio of seismic imaging by applying robust filtering strategies that align and equalize multiple seismic acquisitions over time. By incorporating rigid sparsity constraints, the method captures subtle reservoir changes, reduces noise and artifacts, and improves similarity between vintages. Preliminary results show its potential for more effective monitoring and decision-making in the offshore oil field.

Introduction

Time-lapse (4D) seismic analysis is a well-established technique for monitoring reservoir dynamics throughout the production lifecycle. By comparing seismic volumes acquired at different times, it is possible to infer changes in fluid saturation, pressure, and contact movement, contributing to more efficient reservoir management. However, differences between acquisitions — especially when not planned with identical parameters — can introduce undesired variations in the seismic image. These discrepancies may arise from tidal variations, feathering, source and receiver inconsistencies, vessel speed, positioning, or even geological and anthropogenic effects such as subsidence, erosion, or buildings.

The goal of 4D processing is to minimize these discrepancies under the assumption that the overburden remains unchanged. In practice, however, residual effects often persist and can be quantified using metrics such as NRMS (Normalized Root Mean Square), with values around 15% considered acceptable in streamer acquisitions.

In the final stages of 4D processing, a matching filter is applied to align and equalize the base and monitor datasets. This filter is typically estimated using least squares due to its computational efficiency. However, least squares methods are known to be sensitive to outliers and non-Gaussian noise, motivating the exploration of more robust alternatives.

Method and Theory

The matching filter is applied to enhance the similarity between base and monitor seismic vintages. In the conventional approach, this is formulated as a linear inverse problem $Mr = B$, where M is the convolutional matrix of the monitor data, B is the base data, and r is the filter to be estimated. The regularized least squares (LS) solution can be expressed by:

$$r = (M^{\mathrm{T}}M + \lambda I)^{-1} M^{\mathrm{T}}B$$

where λ is a small positive constant known as whitenoise.

An alternative least-squares-based approach explored in this study is the spectral coherence analysis (SCA), as described by Hoeber et al. (2005). This method estimates the matching filter in the frequency domain by analyzing the coherence between base and monitor datasets. It is particularly effective for identifying and aligning coherent energy across vintages, estimating the signal-to-noise ratio of the data, and serves as a complementary technique to time-domain filtering. Moreover, it can be expanded to match multiple vintages volumes.

While both methods are computationally efficient, they are sensitive to outliers and non-Gaussian noise. To address these limitations, we adopt a robust inversion strategy based on the Iteratively Reweighted Least Squares (IRLS) algorithm, originally proposed by Scales and Gersztenkorn (1988) and extended by Oliveira and Lupinacci (2013) through the incorporation of rigid sparsity constraints in the objective function.

The data misfit Δ_r is defined as: $\Delta_r = B - Mr$. Its L1 norm is approximated by $|\Delta_r| \approx \Delta_r{}^{\mathrm{T}} W_\Delta \, \Delta_r$, where the weight matrix W_Δ is diagonal and defined elementwise as: $W_\Delta = 1/\sqrt{|\Delta_\mathrm{r}|^2 + \varepsilon}$. Here, ε is a small positive constant introduced to ensure numerical stability and to avoid division by zero. This transformation allows the L1 minimization to be reformulated as a weighted L2 problem. Now, defining the objective function ϕ_r with the L1 norm filter penalty, analogous to the data misfit L1 norm approach, as $\phi_r = |\Delta_r| + \mu|r| \approx \Delta_r^T W_\Delta \Delta_r + \mu r^T W_r r$, we insert rigid sparsity to the solution. The IRLS algorithm then solves the matching filter r iteratively using the weighted normal equations from that approach. Follow the formulation:

$$r_k = \left[M^{\mathrm{T}} \left(\frac{I}{\sqrt{|B \, - \, M \, r_{k-1} \,|^2 + \, \varepsilon}} \right) M \, + \, \mu \left(\frac{I}{\sqrt{|r_{k-1}|^2 + \, \varepsilon}} \right) \right]^{-1} M^{\mathrm{T}} \left(\frac{I}{\sqrt{|B \, - \, M r_{k-1} \,|^2 + \, \varepsilon}} \right) B.$$

In this expression r_k is the filter at iteration k, ε approximates the L1 norm and ensures numerical stability, μ is the regularization parameter that controls the sparsity of the solution.

The resulting system is symmetric and positive definite and was solved using Cholesky factorization in its outer product form, as described by Golub and Van Loan (2013). This decomposition expresses the matrix as the product of a lower triangular matrix and its transpose, offering computational efficiency with a cost of $O(n^3)$ floating-point operations (FLOPs) for the factorization, followed by two triangular system solutions at $O(n^2)$ FLOPs each, and enabling parallelization — an important feature for large-scale 4D seismic applications. Although IRLS supports backtracking — at the cost of parameter evaluation — a fixed-step version was adopted.

The dataset used for method validation was extracted from a stage preceding the application of the dynamic time warping correction within the seismic processing flow, which focuses on 4D geophysical analysis of the Marlim Sul field**.** The matching filter was computed locally within a window defined over the overburden interval, where production-related changes are not expected. For each spatial cell, a local filter was estimated and applied to the full seismic trace. While least squares and coherence-based methods required exclusion of the seafloor reflection due to its anomalous amplitudes, the robustness of the IRLS approach allowed its inclusion without compromising stability.

All methods were compared using filters with 64 coefficients. Due to methodological differences, other parameters were not standardized. Notably, the IRLS results presented here include the seafloor reflection in the computation window, whereas the other methods excluded it to maintain numerical stability.

Results

The comparative analysis between the Iterative Reweighted Least Square (IRLS) method and the least-squares-based approaches — regularized Least Squares (LS) and Spectral multi-Coherence Analysis (SCA) — demonstrates the advantages of using robust sparse inversion for 4D seismic response estimation in the Marlim Sul field.

Figure 1 presents the 4D seismic response (monitor minus base) for all methods, displayed side by side respectively: input, IRLS, LS, and SCA. In the overburden region, residual misalignments are still visible in the IRLS result, whereas LS and SCA exhibit lower noise levels in this zone. However, at the reservoir level, the LS-based methods introduce significant noise contamination around the 4D signal, compromising interpretability. In contrast, the IRLS result preserves the integrity of the 4D response, with minimal noise interference in the reservoir zone.

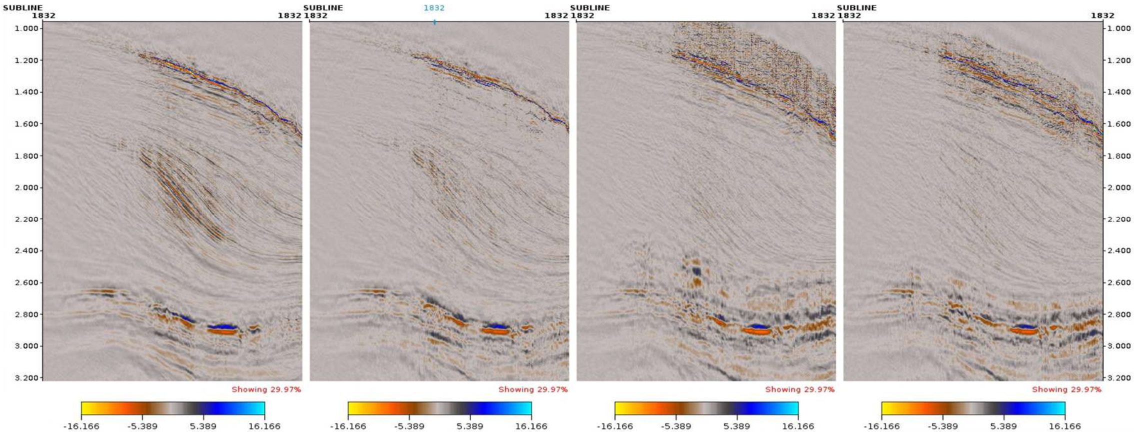

Figure 1: 4D response on the reflectivity seismic image for input, IRLS, LS, SCA respectively.

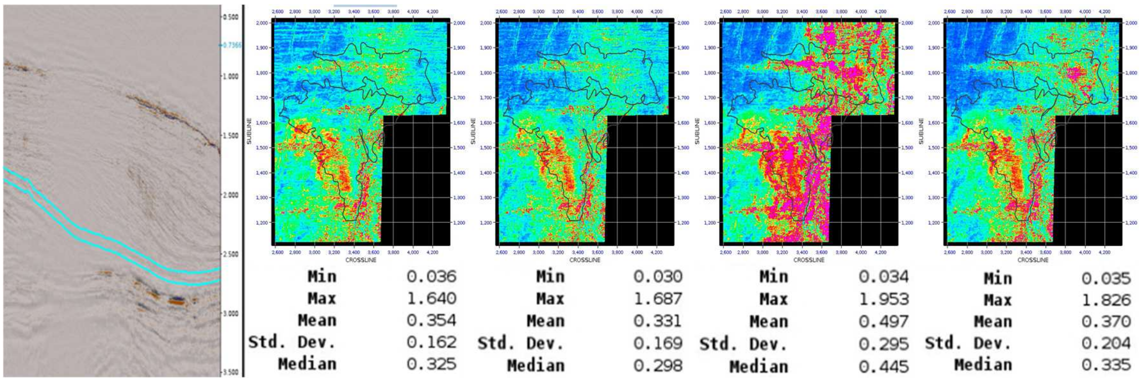

Figure 2: NRMS map from window showed on the seismic image, for input, IRLS, LS and SCA, respectively.

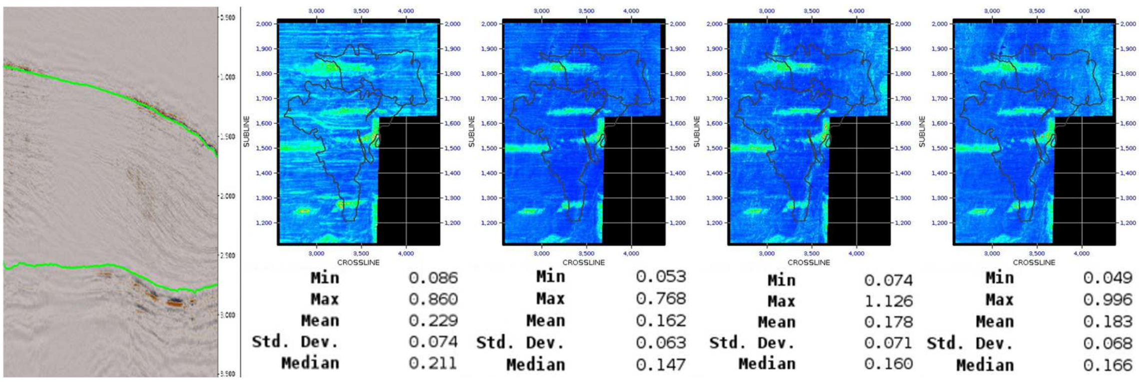

Figure 3: NRMS map from window showed on seismic image, for input, IRLS, LS and SCA, respectively.

Figure 2 shows the seismic section used to define the NRMS computation window, along with NRMS maps overlaid with reservoir outlines. Figure 3 replicates this analysis using an expanded window, whose upper boundary approaches the seafloor. In both cases, the IRLS method yields lower NRMS median values compared to LS and SCA, indicating better temporal consistency, amplitude matching and reduced noise in the matched data.

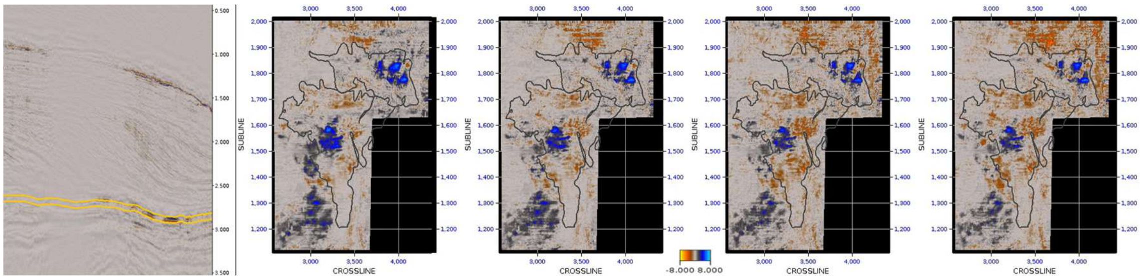

Figure 4: 4D response around the reservoir horizon, showing hardening and softening anomalies, for input, IRLS, LS and SCA, respectively.

Figure 4 displays maps of the difference in RMS amplitude between monitor and base datasets around the reservoir. These maps highlight blue positive hardening anomalies (e.g., oil-to-water substitution, increasing the impedance) expected from production effects. While LS and SCA results show these anomalies contaminated by orange negative surrounding noise, simulating a false softening effect, the IRLS method preserves the spatial coherence of the anomalies, enhancing their interpretability and reliability for reservoir monitoring. Despite the presence of genuine softening anomalies, orange noise also masks them in the LS and SCA results, whereas IRLS reveals them more clearly.

Conclusions

The proposed method was applied to 4D seismic data from the Marlim Sul field and produced less noisy results compared to filters obtained via least squares and spectral coherence analysis, yielding a 4D response with improved signal-to-noise ratio. It also enabled the expansion of the similarity window between vintages, with more favorable NRMS statistics than those achieved by the comparison methods.

Although the method converges rapidly and delivers high-quality results, it incurs a significantly higher computational cost relative to traditional approaches. However, this limitation is mitigated by the method’s compatibility with parallel computing. The IRLS algorithm accepts both Cholesky recursive and non-recursive implementations and can be integrated with iterative solvers such as the conjugate gradient method. Furthermore, it also allows the use of a backtracking strategy, at an extra performance cost. These features make the approach scalable and well-suited for high-performance computing environments, reinforcing its applicability in large-scale 4D seismic processing workflows.

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