Comparison of Seismic Attribute Techniques for Fault Detection with Machine Learning Workflows: a case study from The Sirte Basin, Libya

Abdurahmaan Khalid Ajaj

Petroleum Research Center
ORCID No. (Author): 0009-0005-8763-7470
Email : a.ajaj@prclibya.com

Abstract

Accurate fault interpretation is a fundamental component of seismic structural analysis and is essential for reservoir characterization, structural mapping, and hydrocarbon exploration. This study presents a comparative analysis of conventional seismic attribute-based fault detection and modern machine learning (ML)-assisted interpretation using 3D seismic data from the Sirte Basin, Libya. The study area is characterized by complex structural deformation and predominantly NW–SE-oriented extensional faulting. The conventional workflow applies seismic conditioning, structural smoothing, variance attributes, and Ant Tracking to enhance and automatically extract fault-related discontinuities. In contrast, the ML workflow utilizes deep-learning techniques to identify fault patterns directly from seismic data. The comparison focuses on fault continuity, spatial resolution, noise suppression, detection of subtle faults, and interpretation efficiency. The results demonstrate that conventional attributes provide effective and interpretable fault-enhancement products, while ML-assisted methods can improve fault continuity and reduce noise, particularly for complex and subtle structures. The study highlights the potential of integrating conventional seismic attributes with machine learning to enhance fault interpretation and improve structural understanding of the Sirte Basin.

Keywords: Seismic Attributes, Machine Learning, Fault Detection, Ant Tracking, Structural Interpretation

مقارنة بين تقنيات السمات الزلزالية للكشف عن الصدوع وسير عمل التعلم الآلي: دراسة حالة من حوض سرت، ليبيا

عبدالرحمن خالد عجاج
مركز البحوث النفط ، طرابلس-ليبيا

ملخص

يُعدّ التفسير الدقيق للفوالق أحد العناصر الأساسية للتحليل البنيوي للبيانات الزلزالية، كما يُعتبر مهمًا لتوصيف المكامن، ورسم التراكيب البنيوية، واستكشاف الهيدروكربونات. تقدم هذه الدراسة مقارنة بين أساليب الكشف التقليدية عن الفوالق باستخدام الخصائص الزلزالية وأساليب التفسير الحديثة المعتمدة على التعلم الآلي (ML)، وذلك باستخدام بيانات زلزالية ثلاثية الأبعاد من حوض سرت في ليبيا. تتميز المنطقة بتعقيد بنيوي واضح ووجود فوالق تمددية يغلب عليها الاتجاه شمال غرب–جنوب شرق. يعتمد مسار العمل التقليدي على تهيئة البيانات الزلزالية، والتنعيم البنيوي، وحساب خاصية التباين (Variance)، ثم استخدام تقنية التتبع بالنمل (Ant Tracking) لتعزيز واستخراج الانقطاعات المرتبطة بالفوالق بصورة آلية. في المقابل، يعتمد مسار التعلم الآلي على تقنيات التعلم العميق للتعرف على أنماط الفوالق مباشرةً من البيانات الزلزالية. تركز المقارنة على استمرارية الفوالق، والدقة المكانية، وتقليل الضوضاء، والقدرة على تحديد الفوالق الدقيقة، وكفاءة التفسير. وتوضح النتائج أن الخصائص الزلزالية التقليدية توفر منتجات فعالة وقابلة للتفسير لتعزيز الفوالق، بينما يمكن لأساليب التعلم الآلي تحسين استمرارية الفوالق وتقليل الضوضاء، خاصةً في التراكيب المعقدة والدقيقة. وتبرز الدراسة إمكانية دمج الخصائص الزلزالية التقليدية مع التعلم الآلي لتحسين تفسير الفوالق وتعزيز فهم البنية الجيولوجية لحوض سرت.

الكلمات المفتاحية: خصائص البيانات الزلزالية، التعلم الآلي، الكشف عن الفوالق، خوارزمية تتبع النمل، التفسير البنائي

1. Introduction

Fault interpretation is a key element of seismic structural analysis, with important implications for reservoir characterization, exploration, and development (Chopra & Marfurt, 2007). Faults are zones of discontinuity that can influence reservoir compartmentalization, fluid flow, and well placement. However, their reliable interpretation from seismic data can be difficult because of noise, subtle fault expressions, and complex geometries. Seismic attributes such as variance can highlight discontinuities, while Ant Tracking can help extract fault-like features from attribute volumes (Chopra & Marfurt, 2007; Abdelnabi et al., 2017). Recent deep-learning approaches, including convolutional neural networks, provide another way to identify fault patterns in 3D seismic data (Wu & Famelis, 2019).

1.1 Main Objective

- To compare Machine Learning (ML) workflows with traditional seismic attribute methods, particularly Ant Tracking, for detecting and mapping complex fault networks in the Sirte Basin, Libya.
- To evaluate both workflows in terms of fault detection accuracy, continuity, efficiency, and processing time to identify the most effective approach for seismic fault interpretation.

1.2 Geology of the Sirte Basin

The Sirte Basin is one of the major hydrocarbon provinces in North Africa and is a complex rift system in north-central Libya as shown in Figure 1. Its tectonic evolution includes Late Cretaceous rifting, which formed a network of platforms and troughs. The basin is dominated by NW–SE-oriented normal faults, which influence hydrocarbon migration and trapping. These regional structural characteristics make reliable fault mapping important for exploration and reservoir interpretation (Abadi et al., 2020).

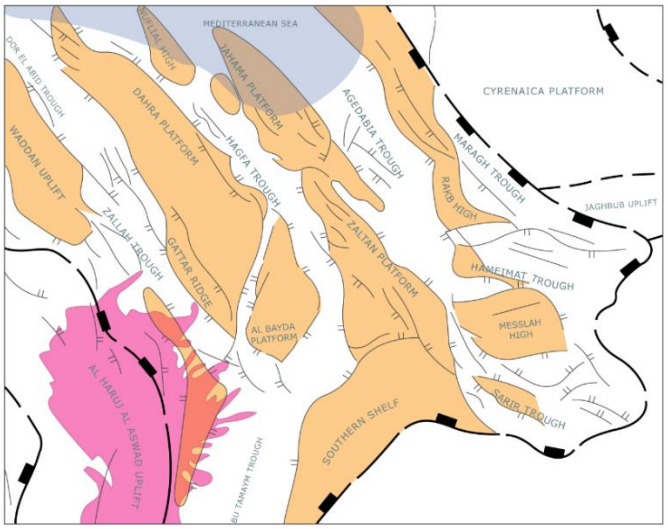


Figure 1: Tectonic elements of The Sirte rift basin & large numbers of significant oil fields

1.3 Challenges in Seismic Fault Interpretation

Traditional manual interpretation can be subjective and time-consuming, while noise and complex fault geometries may obscure discontinuities in seismic amplitude data (Chopra & Marfurt, 2007; Abdelnabi et al., 2017). Key challenges include:

- Seismic Noise: Acquisition and processing artifacts often mask subtle discontinuities.
- Complex Geometries are difficult to resolve using standard amplitude volumes.

- Data Volume: Modern 3D seismic volumes are too large for exhaustive manual interpretation, necessitating high-fidelity automated solutions.

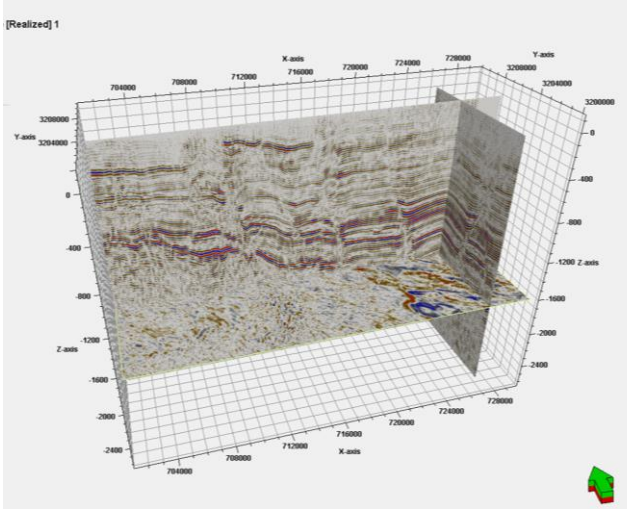


Figure 2 PSTM seismic amplitude volume used in this study.

The amplitude data provides the seismic reflection framework from which structural discontinuities are interpreted; however, faults may not always be clearly visible where signal-to-noise quality is poor. Figure 2 shows the PSTM seismic amplitude volume used in this study.

Machine-learning (ML) techniques have created new opportunities for automating fault detection. Deep-learning models can learn patterns from seismic examples and identify fault-like features that may be difficult to capture with conventional attributes alone (Wu & Famelis, 2019). This paper compares two workflows in the Sirte Basin: a conventional attribute-based workflow using structural smoothing, first derivative and variance attributes followed by Ant Tracking, and a machine-learning workflow that detects fault patterns from seismic data (see Figure 3).

1. The conventional workflow uses structural smoothing, first-derivative and variance (edge-detection) attributes, followed by Ant Tracking for automatic fault extraction. Seismic attributes are commonly used to enhance discontinuities and support fault interpretation (Chopra & Marfurt, 2007; Abdelnabi et al., 2017).

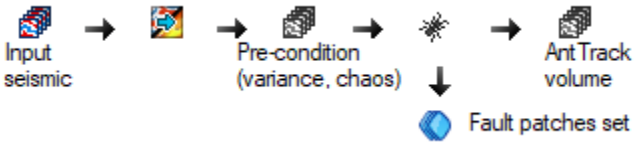


Figure 3: An Ant Tracking for automatic fault extraction workflow.

2. The machine-learning workflow uses a deep-learning model to identify fault patterns from the seismic amplitude volume, as illustrated in Figure 4. CNN-based seismic fault segmentation has been demonstrated in published research (Wu & Famelis, 2019).

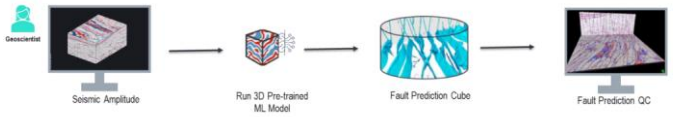


Figure 4: A machine learning-based workflow

2. Dataset and Methodology

2.1 Dataset of This Study

The dataset is a standard Pre-Stack Time Migration (PSTM) seismic amplitude volume. For quality control, 64 key faults were manually interpreted and used as a reference set to compare the outputs of the ML and Ant Tracking workflows (Figure 5).

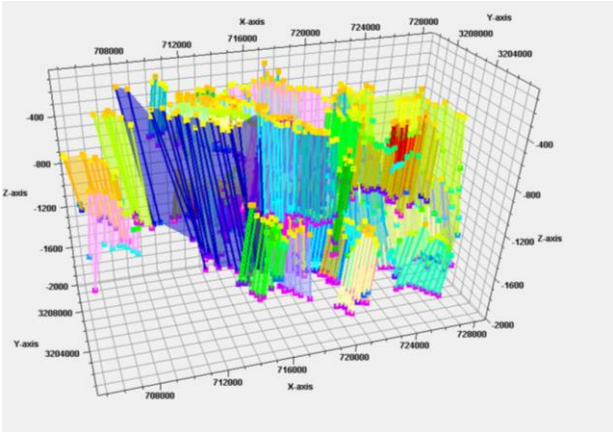


Figure 5: The Manual picked used as a reference to test & QC how well machine learning methods can detect faults.

2.2. Workflow and Methodology

2.2.1 Data Preparation

This study uses 3D seismic volumes from a regional exploration project in the Sirte Basin, Libya. Variable signal-to-noise ratio is a key challenge because it can obscure fault signatures. Two strategies were evaluated: an ML workflow applied to the seismic amplitude data without user-applied filtering or attribute enhancement, and a conventional workflow that uses derived seismic attributes to highlight structural discontinuities. These approaches reflect two different ways of extracting fault-related information from seismic data (Chopra & Marfurt, 2007; Wu & Famelis, 2019).

The fundamental difference between these the methods lies in their approach to data "filtering." The Ant Tracking workflow depends heavily on the interpreter's ability to manually clean and condition the data. While this allows for human oversight, it introduces subjectivity and often leaves gaps in areas where data quality is poor. In contrast, the Machine Learning workflow manages noise and signal enhancement internally through its neural layers. This allows the system to effectively see Figure 6, the seismic artifacts that typically confuse traditional algorithms. Ultimately, by transitioning from a parameter-heavy manual process to a probabilistic AI-driven extraction, the ML approach produces a more efficient and geologically consistent map of the basin's complex fault networks.

2.2.2 Seismic Attribute and Ant Tracking Workflow

The conventional workflow (Figure 6) begins with structural smoothing to reduce random noise while preserving discontinuities. Variance and first-derivative attributes are then calculated to emphasize changes in the seismic signal. The attributes are supplied to Ant Tracking, which enhances connected discontinuities; the resulting volume is thresholded and individual fault surfaces are extracted. Attribute-assisted fault interpretation and Ant Tracking are established approaches for enhancing fault-related features in seismic data (Chopra & Marfurt, 2007; Abdelnabi et al., 2017).

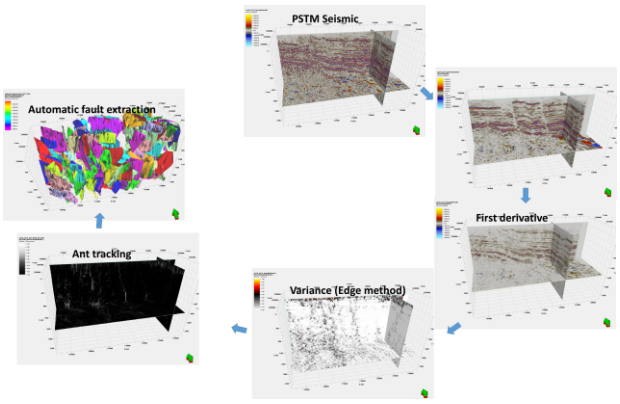


Figure 6: Seismic Attribute and Ant Tracking Workflow

2.2.3 The Machine Learning-Based Workflow

The ML workflow (Figure 7) processes the seismic amplitude volume with a deep-learning model, rather than relying on user-defined seismic attributes as the primary fault indicators. The model generates a fault-probability volume; thresholding and pointset extraction are then used to identify high-probability fault locations and group them into surfaces. CNN-based segmentation of 3D seismic faults has been described by Wu and Famelis (2019). The results in this study are evaluated against the 64 manually interpreted reference faults.

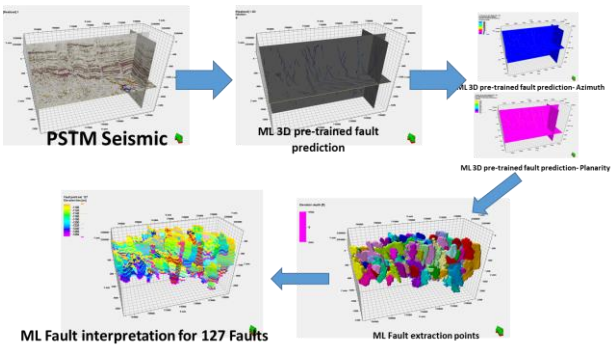


Figure 7: The Machine Learning-Based Workflow

3. Result and Discussion

3.1 Comparison of AI Faults vs. Ant Tracking

The results indicate differences between the two automated workflows. Based on visual comparison with the 64 manually interpreted reference faults, the ML output shows more coherent vertical continuity of the NW–SE fault systems in this dataset. This is a qualitative comparison and should not be interpreted as a quantitative accuracy score because no numerical precision/recall metrics are reported.

In areas with weak or noisy seismic reflections, the Ant Tracking result contains more fragmented or disconnected features. The ML result appears to preserve more connected fault-like surfaces across some of these areas. This observation is consistent with the potential of learned seismic patterns for fault segmentation, although performance remains dependent on the training data and model generalization (Wu & Famelis, 2019).

3.2 Efficiency in Automatic Extraction

From a practical standpoint, the conventional Ant Tracking workflow requires selection and adjustment of attribute and extraction parameters, and the interpreter may need to review and clean the resulting surfaces. This can make the workflow iterative, particularly where noise or complex fault intersections affect the output (Chopra & Marfurt, 2007; Abdelnabi et al., 2017).

The ML workflow can reduce some manual attribute-conditioning and extraction steps, but it still requires appropriate model

training, threshold selection, quality control, and geological review. In this study, the output is visually compared with the reference faults and the Ant Tracking result; processing-time measurements would be needed to quantify any efficiency advantage. As shown in Figure 8, the mixer cube overlays the ML-derived fault interpretation on the raw seismic amplitude data. This view allows the interpreted fault surfaces to be checked against the underlying reflection patterns and helps assess whether the predicted faults follow plausible seismic discontinuities.

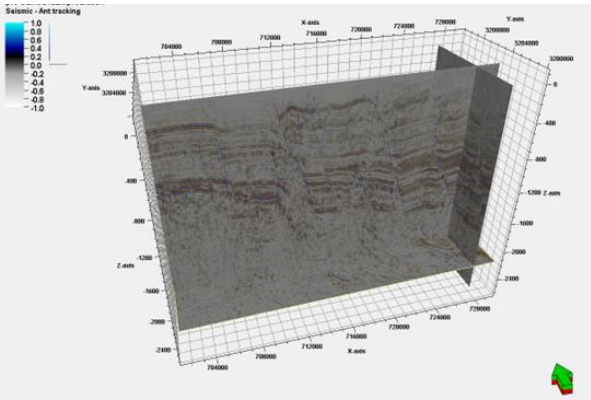


Figure 8: Mixer cube combining the raw seismic amplitude volume and the ML-derived fault cube.

Figure 9 presents the same type of overlay for the Ant Tracking output. Comparing Figures 8 and 9 provides a visual basis for assessing differences in fault continuity, fragmentation, and alignment with the seismic reflections. In this dataset, the ML interpretation appears more connected in some areas, whereas the Ant Tracking result contains more discontinuous features; this is a qualitative visual observation rather than a measured accuracy statistic.

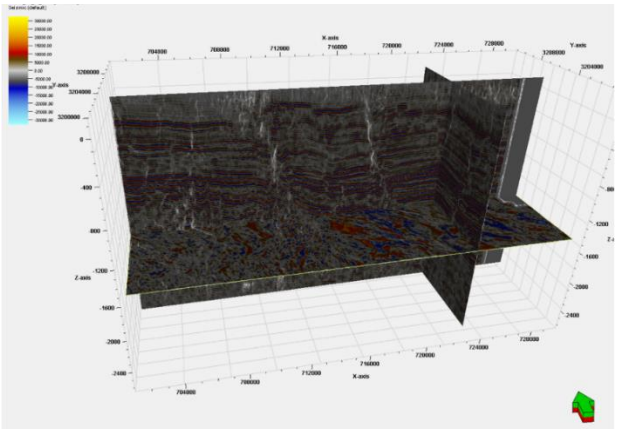


Figure 9: Mixer cube combining the raw seismic amplitude volume and the Ant Tracking fault cube.

3.3 Comparison Criteria

The performance of both workflows was compared using the following criteria:

- **Accuracy**: Evaluated by visual comparison of fault planes with known geological structures and fault markers.
- **Continuity**: Measured by the continuity and length of extracted fault planes, as well as the ability to capture subtle fault traces.
- **Efficiency**: Measured by the processing time required to generate the fault surfaces and the amount of manual intervention needed in each workflow.
- **Time**: The total time taken for each workflow, from data input to final fault surface extraction.

4. Conclusion

This study demonstrates that the evolution of seismic interpretation has reached a pivotal turning point. While traditional seismic

attributes and Ant Tracking have served the industry well—and remain reliable tools for high-quality, "clean" data—they often struggle to meet the demands of geologically complex environments. In a setting as structurally intricate as the **Sirte Basin**, these traditional methods frequently fall short, requiring excessive manual intervention to produce a usable map.

The introduction of Machine Learning **(ML)** represents more than just a new software update; it is a fundamental leap in both efficiency and accuracy. The true power of the ML approach lies in its ability to bridge the gap between human intuition and computational speed. By "learning" from the experience of human interpreters, the model can look at messy or noisy data and see the underlying geological truth that simpler algorithms miss. It doesn't just track lines; it understands the three-dimensional continuity of fault planes.

Ultimately, the ML workflow proves to be the superior choice for modern structural analysis. It handles the "heavy lifting" of data processing at an incredible scale, delivering results that are both highly precise and geologically sound. By reducing the time spent on manual cleanup and repetitive parameter testing, this technology allows geoscientists to focus on the more critical tasks of reservoir characterization and risk assessment, ensuring a more accurate understanding of the subsurface.

5. Recommendation

- Large-Scale Applications: Machine learning should be prioritized for large seismic datasets, where efficiency and automation provide significant advantages in reducing processing time and manual intervention.
- Future Research: Future studies should explore the use of deep learning models, which have shown promise in other domains of seismic interpretation. Additionally, models could be trained on more diverse datasets to enhance the generalization of fault detection in different geological settings.

References

Abadi, M., et al. (2020). Tectonic Evolution and Complex Faulting of the Sirte Basin: Implications for Hydrocarbon Systems. Journal of African Earth Sciences.

Abdelnabi, A., et al. (2017). Seismic Attribute-Aided Fault Detection and Enhancement in the Sirte Basin, Libya. Interpretation, SEG/AAPG.

Alzaruk, A., et al. (2024). Application of Machine Learning for Accelerating the Fault Interpretation in the Structurally Complex Area: A Case Study of the Sirte Basin, Libya. MEOS GEO Technical Programme, SPE-227700.

Chopra, S., & Marfurt, K. J. (2007). Seismic Attributes for Fault/Fracture Characterization. SEG Technical Program Expanded Abstracts.

Wu, X., & Famelis, G. (2019). FaultSeg3D: Using Synthetic Datasets to Train Convolutional Neural Networks for 3D Seismic Fault Segmentation. Geophysics, 84(6), IM13–IM26.